STUDIES ON SOME ASPECTS OF COMPOSITE MACHINING

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By

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Certificate of Approval

This is to certify that the thesis entitled **STUDIES ON SOME ASPECTS OF COMPOSITE MACHINING** submitted by ***Ankita Singh*** has been carried out under my supervision in partial fulfillment of the requirements for the ***Degree of Master of Technology (By Research)*** in ***Production Engineering*** at National Institute of Technology, Rourkela, and this work has not been submitted elsewhere before for any other academic degree/diploma.

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ANKITA SINGH

Abstract

In this technological era, globalization has brought new challenges for the manufacturing industries, towards improving quality and productivity simultaneously, by reducing costs and increasing the performance of the machine tools. Process simulation is one of the most important aspects in any manufacturing/production context. With upcoming worldwide applications of Glass Fiber Reinforced Polymer (GFRP) composites; machining has become an important issue which needs to be investigated in detail. Process efficiency is measured in the sense of different objective functions or process output responses weather they are acceptable for a given targeted value or tolerance. Therefore, finding the best optimal parameter combination can lead towards improvement of the overall process efficiency. The performance of the process can be improved by applying optimization to the simulation model with respect to its process parameters. Single objective optimization method often creates conflict, when more than one response variables need to be optimized simultaneously. In order to minimize cost and to maximize production rate simultaneously; multi-objective optimization approach should be explored. In this thesis, multi-objective optimization methods have been reported to study some aspects of machining of composite material i.e. Glass Fiber Reinforced Polymer (GFRP) composite. The various process parameters used were cutting speed, feed rate, and depth of cut. Optimal cutting condition has been aimed to be evaluated to satisfy contradicting multi-requirements of product quality as well as productivity. This thesis has intended towards focusing two important aspects (i) when it comes to improve productivity, material removal rate has been considered and for (ii) quality of the machined composite product, various surface roughness characteristics of statistical importance have been investigated.

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Chapter 1: Introduction

1.1 Background

Fiber-reinforced polymer (FRP) composite is defined as a combination of a polymer (plastic) matrix (either a thermoplastic or thermoset resin, such as polyester, isopolyester, vinyl ester, epoxy, phenolic) a reinforcing agent such as glass, carbon, aramid or other reinforcing material such that there is a sufficient aspect ratio (length to thickness) to provide a discernable reinforcing function in one or more directions. FRP composite may also contain: fillers, additives, core materials that modify and enhance properties of the final product. The constituent elements in a composite retain their identities (they do not dissolve or merge completely into each other) while acting in concert to provide a host of benefits ideal for structural applications including: high strength and stiffness retention, light weight/parts consolidation, resistance to creep (permanent deflection under long term loading), as well as environmental factors. Composite material can be formed by mixing fibers with resins in a particular defined orientation thereby providing desired mechanical properties to be used in various field of application. Precise knowledge is indeed required to control the parameters involved to achieve those excellent properties.

With the increasing use of fiber reinforced polymer composites outside the defense, space and aerospace industries, machining of these materials is gradually assuming a significant role. The current knowledge of machining FRP composites is in transition phase for its optimum economic utilization in various fields of applications. Therefore, machining and machinability aspects of composites have become the predominant research areas in this field. With increasing applications, economic techniques of production are indeed very important to achieve fully automated large-scale manufacturing cycles. Although FRP composites are usually molded, for obtaining close fits and tolerances and also achieving near-net shape, certain amount of machining has to be carried out. Due to their anisotropy, and non-homogeneity, FRP composites face considerable problems in machining like fiber pull-out, delamination, burning, etc. There is a remarkable difference between the machining of conventional metals and their alloys and that of composite materials. Further, each composite differs in its machining behavior since its physical and mechanical properties depend largely on the type of fiber, the fiber content, the fiber orientation and variability in the matrix material. Considerable amount of literature is readily available on the machinability of (Glass Fiber Reinforced Polymer) GFRP composites; with very limited work on machining parameters optimization for GFRP composites. Therefore, machining process optimization for all types FRP composites is seemed to be an emerging area of research.

In this context, the present research has aimed to highlight multi-objective extended optimization methodologies to be applied in machining of GFRP composites with different machining environments. Attempt has been made to overcome drawbacks/ limitations and assumptions of existing optimization techniques available in literature and to develop a robust methodology for multi-response optimization in GFRP composite machining for continuous quality improvement and off-line quality control. Design of Experiment (DOE) has been selected based on Taguchi's orthogonal array design with varying process control parameters like: spindle speed, feed rate and depth of cut. Multiple surface roughness parameters (those are of statistical importance) of the machined GFRP product along with Material Removal Rate (MRR) of the machining process have been optimized simultaneously.

1.2 State of Art (International and National Status)

Literature provides a strong impression in relation to the scope as well as interest in the field of composite machining. Various aspects on composite machining were addressed by pioneer researchers throughout the World. **Rahaman et al. (1999)** studied on machinability aspects of carbon fiber reinforced composite. Three types of cutting tool inserts: uncoated tungsten carbide, ceramic and cubic boron nitride (CBN) were used to machine short (discontinuous) and long (continuous) fiber carbon epoxy composites. **Ferreira et al. (1999)** studied the performance of different tool materials such as ceramics, cemented carbide, cubic boron nitride (CBN), and diamond (PCD). The results showed that only diamond tools were suitable for use in finish turning. An optimization methodology was used in rough machining to determine the best cutting conditions. It was concluded that the optimization of the cutting conditions is extremely important in the selection of the tools and cutting conditions to be used in the CFRP manufacturing process.

Enemuoh et al. (2001) presented a new comprehensive approach to select cutting parameters for damage-free drilling in carbon fiber reinforced epoxy composite. The approach was based on a combination of Taguchi's experimental analysis technique and a multi-objective optimization criterion. The optimization objective included the contributing effects of the drilling performance measures: delamination, damage width, surface roughness, and drilling thrust force. **Davim et al. (2004)** studied the cutting parameters (cutting velocity and feed rate) under specific cutting pressure, thrust force, damage and surface roughness in Glass Fiber Reinforced Polymers (GFRP's). A plan of experiments, based on the techniques of Taguchi, was established considering drilling with prefixed cutting parameters in a hand lay-up GFRP material. The analysis of variance (ANOVA) was performed to investigate the cutting characteristics of GFRP's using Cemented Carbide (K10) drills with appropriate geometries. **El-Sonbaty et al. (2004)** investigated the influence of cutting speed, feed, drill size and fiber volume fraction on the thrust force, torque and surface roughness in drilling processes of fiber-reinforced composite materials.

Davim and Mata (2005a) optimized surface roughness in turning of FRP tubes manufactured by filament winding and hand lay-up, using polycrystalline diamond cutting tools. Additionally, the optimal material removal rates were obtained through multiple analysis regression (MRA). In another paper, **Davim and Mata (2005b)** studied on the machinability in turning processes of fiber reinforced polymers (FRPs) using polycrystalline diamond cutting tools. Controlled machining experiments were performed with cutting parameters prefixed in the work piece. A statistical technique, using orthogonal arrays and analysis of variance, was employed to investigate the influence of cutting parameters on specific cutting pressure and surface roughness.

Zitoune et al. (2005) made experimental analysis of the orthogonal cutting applied to unidirectional laminates in carbon/epoxy for various angles between the direction of fibers and the tool cutting direction (cutting speed). The numerical modeling of the orthogonal cutting in statics for the simple case of fibers orientated at 0° with respect to the tool's cutting direction was also attempted. The experimental study highlighted great influence of the angle between the fiber orientation and the direction of cutting speed of the tool on the chip formation as well as the rupture modes. **Bagci and Işık (2006)** carried out orthogonal cutting tests on unidirectional glass fiber reinforced polymers (GFRP), using Cermet tools. During the tests, the depth of cut, feed rate, and cutting speed were varied, whereas the cutting direction was held parallel to the fiber orientation. Turning experiments were designed based on statistical three-level full factorial experimental design technique. An artificial neural network (ANN) and response surface (RS) model were developed to predict surface roughness on the turned part surface.

Davim and Mata (2007) investigated the machinability in turning processes of glass fiber reinforced polymers (GFRP's) manufactured by hand lay-up. The machinability of these materials in function of cutting tool (polycrystalline diamond and cemented carbide tools) was studied.

Tsao and Hocheng (2008) highlighted the prediction and evaluation of thrust force and surface roughness in drilling of composite material using candle stick drill. The approach was based on Taguchi method and the artificial neural network. A correlation was established between the feed rate, spindle speed and drill diameter with the induced thrust force and surface roughness in drilling composite laminate. The correlations were obtained by multi-variable regression analysis and radial basis function network (RBFN) and compared with the experimental results. **Rubio et al. (2008)** employed high speed machining (HSM) to realize high performance drilling of glass fiber reinforced plastics (GFRP) with reduced damage to assess delamination. **Sheikh-Ahmad and Yadav (2008)** presented the mechanistic modeling approach for predicting cutting forces in the milling process of carbon fiber reinforced composites. Specific energy functions were determined by regression analysis of experimental data and a cutting model was developed. It was shown that the model was capable of predicting cutting forces in milling of both unidirectional and multidirectional laminates. Model predictions were found to be in good agreement with experimental results.

Davim et al. (2009) provided a better understanding of the machinability of PA 66 polyamide with and without 30% glass fiber reinforcing, when precision turning at different feed rates and using four distinct tool materials. The findings indicated that the radial force component presented highest values, followed by the cutting and feed forces. The PCD tool provided the lowest force values associated with best surface finish, followed by the ISO grade K15 uncoated carbide tool with chip breaker when machining reinforced polyamide. Continuous coiled micro-chips were produced, irrespectively of the cutting parameters and tool material employed. **Ariffin et al. (2009)** focused on optimization of drilling process for the glass fiber reinforced polymer (GFRP) composite sandwich panel. The study provided machinist with a simple procedure in order to minimize the damage events occurring during drilling process for composite material. **Marques et al. (2009)** studied the performance of, four different drills- three commercial and a special step (prototype) that were compared in terms of thrust force during drilling and delamination. **Mata et al. (2010)** applied response surface methodology to predict the cutting forces in turning operations using TiN-coated cutting tools under dry conditions where the machining parameters were cutting speed ranges, feed rate, and depth of cut. Based on statistical analysis, multiple quadratic regression model for cutting forces was derived with high preferment for predicting cutting forces.

India is not far behind in research on the field of composite machining. **Santhanakrishnan et al. (1988)** carried out face turning on glass fiber reinforced plastics (GFRP), carbon fiber reinforced plastics (CFRP) and kevlar fiber reinforced plastics (KFRP) cylindrical tubes to study their machined surfaces for possible application as friction surfaces. The mechanisms of material removal and tool wear are also discussed and illustrated with scanning electron micrographs. The cutting forces encountered during machining of composites were also investigated.

Palanikumar et al. (2004) focused on the optimization of machining parameters for surface roughness of glass fiber reinforced polymers (GFRP) using design of experiments (DOE). The machining parameters considered were speed, feed, depth of cut and work piece (fiber orientation). Attempt was made to analyze the influence of factors and their interactions during machining. The study revealed the optimal combination of machining parameters and to improve the machining requirements of GFRP composites. **Mohan et al. (2005)** outlined the Taguchi optimization methodology, applied to optimize cutting parameters in drilling of glass fiber reinforced composite material. Analysis of variance (ANOVA) was used to study the effects of process parameters on machining process. The drilling parameters and specimen parameters evaluated were speed, feed rate, and drill size and specimen thickness.

Jawali et al. (2006) fabricated a series of short glass fiber reinforced nylon 6 composites with different weight ratios of glass content by melt mixing. The fabricated nylon 6 composites were characterized for physicomechanical properties such as specific gravity, tensile properties, and wear resistance. A marginal improvement in tensile strength and tensile modulus was observed with increase in high modulus fiber. Wear resistance was found to be increased with the increase in rigid glass fiber content in the nylon matrix. The dimensional stability of the composite was found improved with the increase in fiber content. **Palanikumar et al. (2006)** assessed the influence of machining parameters on the machining of GFRP composites using coated Cermet tool inserts. **Palanikumar and Davim (2007)** developed a mathematical model to predict the tool wear on the machining of GFRP composites using regression analysis and analysis of variance (ANOVA) in order to study the main and interactive effect of machining parameters, viz., cutting speed, feed rate, depth of cut and fiber orientation angle of the work piece. **Palanikumar (2007)** attempted to establish model for the surface roughness through response surface method (RSM) in machining GFRP composites.

Karnik et al. (2008) presented application of artificial neural network (ANN) model to study the machinability aspects of unreinforced polyetheretherketone (PEEK), reinforced polyetheretherketone with 30% of carbon fibers (PEEK CF 30) and 30% of glass fibers (PEEK GF 30) machining. A multilayer feed forward ANN was employed to study the effect of parameters such as tool material, work material, cutting speed and feed rate on two aspects of machinability, namely, power and specific cutting pressure. **Palanikumar (2008a)** used Taguchi and response surface methodologies for minimizing the surface roughness in machining glass fiber reinforced (GFRP) plastics with a polycrystalline diamond (PCD) tool. The cutting parameters used are cutting speed, feed and depth of cut. A second-order model was established between the cutting parameters and surface roughness using response surface methodology. **Basheer et al. (2008)** presented an experimental work on the analysis of machined surface quality on Al/SiCp composites leading to an artificial neural network-based (ANN) model to predict the surface roughness. The predicted roughness of machined surfaces based on the ANN model was found to be in very good agreement with the unexposed experimental data set.

Palanikumar et al. (2008) presented a study of influence of cutting parameters on surface roughness parameters such as R_a, R_t, R_q, R_p and R_{3z} in turning of glass fiber reinforced composite materials. Empirical models were developed to correlate the machining parameters with surface roughness. In another paper, **Palanikumar (2008b)** used fuzzy logic for modeling machining parameters in machining glass fiber reinforced plastics by poly-crystalline diamond tool. An L_{27} orthogonal array was used to investigate the machining process with selected cutting parameters: cutting speed, feed, and depth of cut. The output responses considered for the investigation were surface roughness parameters such as arithmetic average height (R_a) and maximum height of the profile (R_t). Fuzzy rule based models were developed for correlating cutting parameters with surface roughness parameters.

Krishnaraj (2008) conducted drilling experiments with drill points, namely standard twist drill, Zhirov-point drill, and multifacet drill, using wide range of spindle speed, and feed rate to analyze thrust force, delamination and surface roughness. **Sait et al. (2009)** proposed an approach for optimizing the machining parameters on turning glass fiber reinforced plastic pipes. Optimization of machining parameters was done by an analysis called desirability function (DF) analysis, which is a useful tool for optimizing multi-response problems. Based on Taguchi's L_{18} orthogonal array, turning experiments were conducted for filament wound and hand layup GFRP pipes using K20 grade cemented carbide cutting tool. The machining parameters such as cutting velocity, feed rate and depth of cut were optimized by multi-response considerations namely surface roughness, flank wear, crater wear and machining force. A composite desirability value was obtained for the multi-responses using individual desirability values from the desirability function analysis. Based on composite desirability value, the optimum levels of parameters were identified. Thus, the application of desirability function analysis in Taguchi technique proved to be a useful tool for optimizing the machining parameters of GFRP pipes.

In another reporting, **Palanikumar and Davim (2009)** assessed the factors in influencing tool wear on the machining of GFRP composites. The machining experiments were carried out using the factors: cutting speed, fiber orientation angle, depth of cut and feed rate. A procedure was developed to assess and optimize the chosen factors to attain minimum tool wear by incorporating (i) response table and effect graph; (ii) normal probability plot; (iii) interaction graphs; (iv) Analysis of Variance (ANOVA) technique. The results indicated that cutting speed showed greater influence on tool flank wear, followed by feed rate.

Singh et al. (2009) reported experimental work conducted using 8 Facet Solid Carbide drills based on L_{27} orthogonal array. The process parameters investigated were spindle speed, feed rate and drill diameter. Fuzzy rule based model was developed to predict thrust force and torque in drilling of GFRP composites. **Hussain et al. (2010)** developed a surface roughness prediction model for the machining of GFRP pipes using response surface methodology (RSM). Experiments were conducted through the established Taguchi's Design of Experiments (DOE) on an all geared lathe using carbide (K20) tool. The cutting parameters considered were cutting speed, feed, depth of cut, and work piece (fiber orientation). A second order mathematical model in terms of cutting parameters was developed using RSM.

Rajasekaran et al. (2011) investigated on machining of carbon fiber reinforced polymer (CFRP) composites to examine the influence of machining parameters combination so as to obtain a good surface finish in turning of carbon fiber reinforced polymer composite by cubic boron nitride (CBN) cutting tool and to predict the surface roughness values using fuzzy modeling. The results indicated that the fuzzy logic modeling technique could be effectively used for the prediction of surface roughness in machining of CFRP composites.

1.3 Motivation and Objective

Fiber-reinforced plastics (FRPs) are used in structural components in various fields of application of mechanical engineering, such as automobile, biomechanics and aerospace industries. Their own properties, particularly the high strength and stiffness and simultaneously low weight, allows the substitution of the metallic materials in many cases. As a result of these properties and potential applications, exists a great necessity to investigate the machining of these composite materials **(Palanikumar, 2008a)**.

In modern-day engineering, high demands are being placed on components made of fiber-reinforced plastics (FRPs) in relation to their dimensional precision as well as to their surface roughness **(Spur and Wunsch, 1988)**. The exact degree of surface roughness can be of considerable importance, because it affects the functionality of the component **(Abouelatta and M´adl, 2001)**. Surface roughness is a great influence on the performance of the mechanical pieces and on the production costs. For these reasons research developments have been carried out with the objective of optimizing the cutting parameters, to obtain a determined surface roughness **(Abouelatta and M´adl, 2001; Erisken, 1999)**. It was found that surface roughness and profile are highly dependent on the fiber orientation (45◦ or 180◦) **(Mata and Davim, 2003)**, the type of fibers **(Jahanmir et al., 1998)** and the measurement direction. The roughness of the machining surface of filament-wound tubes is more sensitive to increasing the winding angle than to increasing the tool feed rate **(Spur and Wunsch, 1988)**.

Machining glass fiber composite is still a major problem, because of their inert nature, high hardness, and refractoriness **(Jain et al., 2002)**. Because of their different applications, the need for machining FRP material has not been fully eliminated. Glass fiber reinforced plastics (GFRPs) are extremely abrasive; thus proper selection of the cutting tool and cutting parameters is very important for a perfect machining process **(Davim et al., 2009)**. The mechanism of machining GFRP composite is quite different from that of metals **(Palanikumar, 2008a; Geier, 1994; Lee, 2001)**. While machining a GFRP, the strong fiber materials cause rapid tool wear and poor surface finish. Tool wear reduction is an important aspect in machining GFRP composites (**Palanikumar and Davim, 2009)**. The surface integrity of a GFRP machined composite is hard to control, including surface roughness, residual stresses and subsurface damages due to varying mechanical properties of the fiber and the matrix **(Zhang, 2009)**. **Santhanakrishnan et al. (1989)** reported that the mechanisms associated with machining of GFRP composite are plastic deformation, shearing and rupture of fibers orientation. Fiber orientation is an important criterion which affects the machining process and strength of the composite **(Bhatnagar, et al., 1995; Venu Gopala Roa, 2003)**. **Sharma et al. (2009)** stated that wear performance of the cutting tool decreases with 90° fiber orientation. **Sreejith et al. (2007)** observed that the cutting force and the cutting temperature affect the performance of the cutting tools while machining carbon/carbon composites. **Hussain et al. (2010)** reported that when GFRP composites are machined, discontinuous chips in powder form are produced, which is entirely different from machining of metals. The machining of GFRP composites differ from machining of metals, because they are anisotropic and inhomogeneous materials.

Aforesaid sections deal with the critical issues/problems in machining GFRP composites, the types of chips that are generally observed and why surface roughness is possibly a greater concern during composite machining. Therefore, machining of composite (GFRP) has been selected as the topic of interest in this present dissertation.

Machining of polymer composites is an indispensable interdisciplinary relevance for process design, tool and production engineers in composite manufacturing. A number of papers are readily available related to the growth of theory and practices on various aspects of composite machining. Literature reveals that aspects of composite machining belong to a wide field with inter-disciplinary, multi-criteria decision-making complexity, and designing a framework has always been a challenging issue. Four basic trends in research on machining and machinability of composites, highlighted in literature are as follows:

a. Mechanics of chip formation and the critical influence of composite architecture on chip formation mode, cutting forces and surface quality
b. The phenomena of tool wear and an analysis of tool materials, tool wear mechanisms in machining of FRP composites
c. Machinability of FRP composites by traditional and nontraditional methods including turning, milling, drilling, abrasive, abrasive water jet and laser machining
d. The issue of health and safety in machining of FRP composites

Literature highlights that extensive efforts have been rendered by previous investigators on various aspects of composite machining. Machinability aspects on a wide variety of FRP composites with different cutting tool materials have been mostly investigated in various machining operations like: turning, drilling, milling etc. Effort has been made to study the influence of controllable process parameters on various aspects of machining performance like: tool wear, cutting forces, surface roughness, delamination etc. Mathematical models have also been developed to understand functional relation among process parameters with aforesaid process responses. Effects of process parameters on flank, crater wear, interaction of various cutting forces (cutting force, feed force etc.) have been studied in detail. Roughness modeling has been reported too; but mostly it is based on centre line roughness average (R_a). But surface quality (integrity) consists of multiple statistical measures like: R_z, R_{ku}, R_{sm}, R_{z1max}, R_{sk} which need to be investigated in detail for better understanding of the machining process behavior on composites. Therefore, there exists scope for optimizing aforesaid multiple surface-roughness features **(Sahoo, 2005)** to achieve desired surface finish. Apart from tool life-tool wear, cutting force interaction and surface roughness; another aspect of machining operation is the material removal rate (MRR) which is directly related to productivity. There must be an optimal balance between product quality and productivity.

Optimization aspects of composite machining have been highlighted in literature, but to a limited extent. In most of the cases optimization has been performed on a single objective function. But in practice, it has been found that optimizing one response may not be favorable for other response(s) on that particular optimal parameter setting. This invites complexity to the multi-objective optimization problem towards optimizing multiple objective functions (may be contradicting in nature) simultaneously.

Literature highlights that Taguchi method **(Datta et al., 2008a)** is very popular in product/process optimization as it requires a well balanced experimental design (limited number of experiments) which saves experimental time as well as experimentation cost. Not only this, Taguchi approach finds optimal at discrete levels of the process parameters; which can easily be adjusted in the machine/ setup. But this method fails to solve multi-objective optimization problems. In order to overcome this, grey relation theory **(Datta et al., 2008b)**, desirability function approach **(Derringer, 1980; Datta et al., 2006)**, utility theory **(Kumar et al., 2000; Walia et al., 2006)** have been applied by previous investigators in combination with Taguchi method. The purpose is to aggregate multiple responses (objective functions) into an equivalent quality index (single objective function) which can easily be optimized using Taguchi method.

In this aggregation procedure, individual priority weights are required to be assigned. In practice, these responses may not be of equally important. Degree of importance/ priority of various responses depend on application area and functional requirements of the product. Assignment of response priority weights basically depends on the discretion of the decision maker (DM). Change in value of the priority weights may yield alteration in the value of aggregated quality-performance index. Entropy measurement technique was applied by **(Datta et al., 2009a)** for evaluation of response weights but it was seen that for a narrow experimental domain it could not work. Moreover, this method invites computational complexity as well.

Existing optimization approaches are based on the assumption that responses are uncorrelated. Interdependence of the responses has been assumed negligible; while in practice any change in one response remarkably affects another response. Thus assumption of negligible response correlation may create imprecision, uncertainty as well as vagueness in the solution. To solve the inter-correlation problem, PCA may be a useful statistical technique for examining the relationships within a given data set of multiple-performance-characteristic (MPC). A new set of uncorrelated data of MPC, called principal components (PCs) can be derived by PCA in descending order of their ability to explain the variance of the original dataset. But when more than one individual PCs show considerable accountability proportion; aggregation of PCs is difficult **(Su and Tong, 1997; Datta et al., 2009b; Routara et al., 2010)**. To overcome this Weighted Principal Component Analysis (WPCA) has been proposed. WPCA is based on the assumption that accountability proportion of individual PCs is treated as individual response weights **(Liao, 2006)**.

Moreover, **Lu and Antony (2002)** presented a procedure for optimizing MPC problems, using the fuzzy multi-attribute decision making process. This procedure can reduce human uncertainties, but requires rather complicated mathematical computations and is relatively difficult for individuals to implement, unless they have adequate mathematical training. Using fuzzy logic analysis **(Zadeh, 1976; Mendel, 1995; Cox, 1992, Yager and Filev, 1999)**, MPCs can be easily dealt with by setting up a reasoning procedure for each performance characteristic and transforming them all into a single value of multiple performance characteristics indices (MPCIs). But correlation aspects among responses cannot be taken care of by fuzzy system unless these are eliminated initially.

It is, therefore, indeed required to develop an efficient model which can efficiently overcome several drawbacks of existing optimization methodologies reported in literature.

In this context, the present study attempts to establish models of integrated optimization procedural hierarchy towards machining of glass fiber reinforced polyester as well as epoxy composites under various machining environment. Several machining performance measures related to quality as well as productivity have been taken under consideration.

The topic is truly an interdisciplinary subject and possesses tasks of challenging nature for production and industrial engineers because of involvement of multi-objective optimization.

1.4 Organization of the Thesis

The entire thesis has been organized in seven chapters. **Chapter 1** presents the background of research on composite machining. An extensive literature survey also depicts the necessity of developing an efficient integrated optimization methodology applicable in product/process optimization in manufacturing/production context. Machining of GFRP composites has been selected here as a case study. **Chapter 2** covers the presentation of necessary mathematical background in understanding Taguchi's philosophy, utility theory, desirability function approach, TOPSIS method, Principal Component Analysis (PCA) and Fuzzy Inference System (FIS). **Chapter 3-5** represent various case studies followed by development of a variety of multi-objective optimization philosophies on machining of composites. **Chapter 6** attempts prediction modeling in machining GFRP composites using Adaptive Neuro-Fuzzy Inference Systems (ANFIS). The coverage of these chapters have been reported as follows.

Chapter 3

Multi-Criteria Decision Making (MCDM) is a methodology to compare, select and rank multiple alternatives that involve disproportionate criteria attributes. Among various MCDM approaches, TOPSIS (*technique for order preference by similarity to ideal solution*) can be efficiently used to identify the best alternative solution from a finite set of points.

In this chapter, ***TOPSIS based MCDM*** approach has been adopted in combination with Taguchi's robust design philosophy to optimize multiple surface roughness parameters of machined GFRP polyester composites. TOPSIS has been used to convert multiple responses to a single preference number which has been treated as Multi-Performance Characteristic Index (MPCI). MPCI has been optimized finally by the Taguchi method. The proposed methodology and the result obtained thereof has been illustrated in detail.

Chapter 4

Taguchi method is frequently used in product/ process design optimization. This method explores the concept of (Signal-to-Noise) S/N ratio to optimize the given process control parameters with respect to an objective function (called response) via reduction in variances. In practice, a product or process is generally consists of a number of conflicting responses while Taguchi method fails to overcome such a multi-response optimization problem. It is therefore, essential, that an equivalent aggregated index has to be determined (by logical accumulation of multiple responses) which can be finally optimized by Taguchi method. The objective of this chapter is to highlight an integrated approach for optimization of multi-responses during machining of glass fiber reinforced polymer (GFRP) composites. Several cutting parameters are indeed responsible for quality as well as productivity aspects of any machining process. Therefore, it is necessary to find an optimal setting of process parameters to ensure the best machining condition in a mass production line. Three process parameters i.e. speed, feed and depth of cut has been considered, in the present study, for optimizing Material Removal Rate (MRR) and average surface roughness (R_a) of the machined GFRP polyester composite product. ***Desirability function and utility theory based on fuzzy approach*** in combination with Taguchi's robust optimization tool have been recommended to avoid the uncertainty and vagueness in solutions that may appear in using existing optimization methodologies, available in literature. The optimal cutting condition for minimizing the surface roughness and maximizing the material removal rate has been determined.

Chapter 5

This chapter proposes an extended multi-objective optimization philosophy applied in a case study of machining (turning) of randomly oriented GFRP polyester composites. Design of Experiment (DOE) has been selected based on Taguchi's L_9 orthogonal array design with varying process control parameters like: spindle speed, feed rate and depth of cut. Multiple surface roughness parameters of the machined FRP product along with Material Removal Rate (MRR) of the machining process have been optimized simultaneously. A ***Principal Component Analysis (PCA) coupled with Fuzzy Inference System (FIS)*** has been proposed for providing feasible means for meaningful aggregation of multiple objective functions into an equivalent single performance index. This Multi-Performance Characteristic Index (MPCI) has been optimized using Taguchi method.

Chapter 6

Recently, the worldwide globalization and erotic development in the technological field has created immense market competition. Industries are now concerned on focusing towards refined product quality and increased productivity. In a mass production line, selection of appropriate parameter setting is indeed essential to avoid compromise in terms of quality as well as productivity. Product quality generally consists of multiple features which may be conflicting in nature depending on the requirements. Hence, achieving high quality product is definitely a challenging job. It is fact that various quality features are mutually correlated and assignment of priority importance of individual quality features is uncertain and vague due to subjective judgment of the decision-makers. Therefore, fuzziness arises and may adversely affect the solution.

Surface roughness plays an important role in determining the interaction between the real object and surrounding environment. Decrease in surface roughness usually increases manufacturing costs exponentially, which results in a trade-off between the manufacturing cost of a component and its performance in application. Direct and on-line measurement of the surface roughness is very difficult. It is therefore, indeed necessary to develop a robust, autonomous and accurate predictive system. In this context, this chapter highlights application of integrated intelligent techniques i.e. ***neural network and the fuzzy inference system called ANFIS*** for prediction modeling of surface roughness as well as material removal rate (MRR) in composite machining. MRR is an important machining performance measure which is directly related to productivity. An experimental data set has been obtained by taking machining parameters like spindle speed, feed rate and depth of cut as input; and surface roughness of the machined glass fiber reinforced epoxy composite product (along with MRR) has been treated as output. Experimental data have been utilized for prediction-modeling of the surface roughness with an accuracy of 91%.

Conclusion of aforesaid works as well as their limitations has been delivered at each chapter ending. Overall conclusion and scope for future work have been highlighted in **Chapter 7**. Finally, the outcome of the present research has been furnished in terms of publications in different journals as well as conference proceedings in a separate list.

Chapter 2: Methodologies Applied

2.1 Taguchi's Philosophy

Dr. Genichi Taguchi, a Japanese management consultant developed an efficient methodology to optimize quality characteristic and is widely being applied now-a-days for continuous improvement and off-line quality control of any manufacturing/production process or product. Taguchi's concepts are as follows:

1. Quality should be designed into the product and not inspected into it.
2. Quality is best achieved by minimizing the deviation from the target. It is immune to uncontrollable environmental factors.
3. The cost of quality should be measured as a function of deviation from the standard and the losses should be measured system-wide.

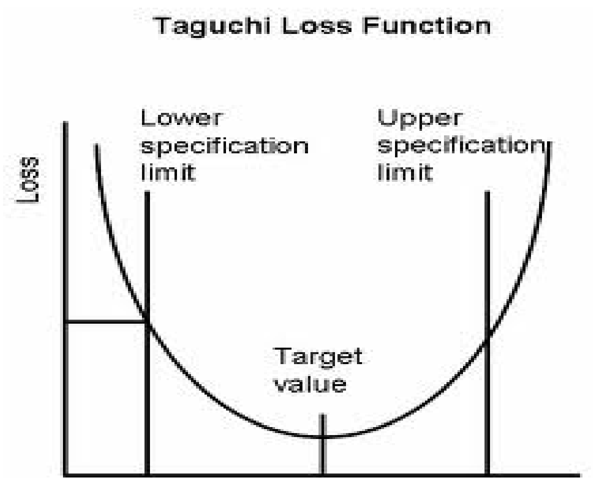


Figure 2.1: Taguchi's quadratic loss function

Taguchi method combines the experiment design theory and quality loss functions to apply for the robust design of products and process. **Fig. 2.1** reflects Taguchi's quadratic quality loss function. Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with a limited number of experiments.

The change in the quality characteristic of a product responsive to a factor introduced in the experimental design is termed as the **Signal** of the desired effect. The effect of the external factors of the outcome of the quality characteristic under test is denoted as N**oise**. To use the loss function as a figure of merit an appropriate loss function with its loss constant must be established which is not always cost effective and easy. The experiment results are then transformed into a **Signal-to-Noise (S/N) ratio**. Taguchi recommends the use of S/N ratio to measure the quality characteristics deviating from the desired value. The S/N ratio for each level of process parameters is computed based on the S/N analysis and converted into a single metric. The aim in any experiment is to determine the highest possible S/N ratio for the result irrespective of the type of the quality characteristics. A high value of S/N implies that signal is much higher than the random effect of noise factors. In Taguchi method of optimization, the S/N ratio is used as the quality characteristic of choice.

Taguchi's techniques have been widely used in engineering design **(Ross, 1996; Phadke, 1989)**. Taguchi's approach to design of experiments is easy to be adopted and applied for users with limited knowledge of statistics; hence it has gained a wide popularity in the engineering and scientific community. The applications of Taguchi technique in the field of materials processing and parametric optimization have been listed in references **(Yang and Tarng, 1998; Su et al., 1999; Nian et al., 1999; Lin, 2002; Davim, 2003; Ghani et al., 2004)**.

According to Taguchi,

Quality characteristics are of three types as shown below.

1. Nominal-is-the-Best (NB) or Target-is-the-Best (TB)
2. Lower-the-Better (LB)
3. Higher-the-Better (HB)

Nominal-is-the-Best (NB) or Target-is-the-Best (TB)

In this case, the closer to the target value, the better is the quality. It does not matter whether the deviation is above or below the target value. Under this circumstance the deviation is assumed quadratic. The following graph **(Fig. 2.2)** portrays quality loss function for Nominal- the-Best (NB) characteristics. Example of NB characteristic may be diameter of a shaft.

The formula for these characteristics is: $\frac{S}{N} = 10 \log \frac{y}{S_y^2}$ **(2.1)**

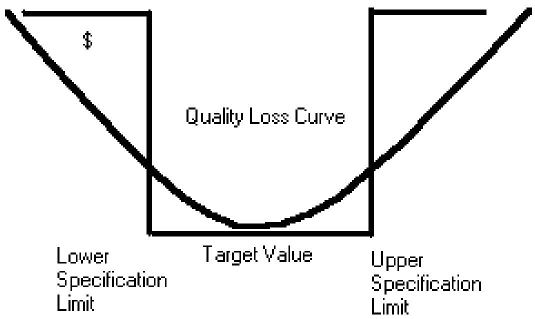


Figure 2.2: Nominal-is-the-Best or Target-is-the-Best characteristic

Lower-the-Better (LB)

The Lower-the-Better (LB) approach holds when a characteristic desires smaller values. As the value gets larger, the loss incurred grows.

Figure 2.3: Lower-the-Better (LB) characteristic

The formula for these characteristics is: $\frac{S}{N} = -10\log\frac{1}{n}\sum y^2$ **(2.2)**

The following graph **(Fig. 2.3)** portrays quality loss function for Lower-the-Better (LB) characteristics. Example of LB characteristic is the amount of impurity in water.

Higher-the-Better (HB)

Higher-the-Better (HB) occurs when a quality characteristic desires higher values. For example, employee participation and the customer acceptance rate are desired to be as high as possible. Under this approach the larger the characteristic value, the smaller be the quality loss.

The formula for these characteristics is: $\frac{S}{N} = -10\log\frac{1}{n}\sum\frac{1}{y^2}$ **(2.3)**

The following graph **(Fig. 2.4)** portrays Higher-the-Better (HB) characteristic and associated quality loss function.

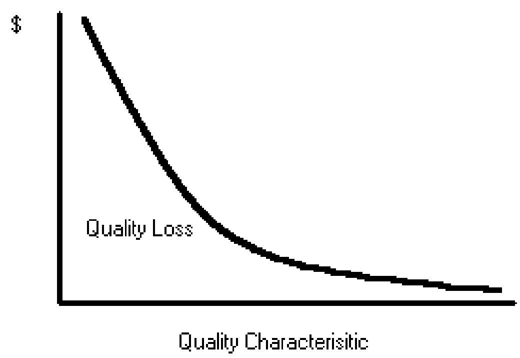


Figure 2.4: Higher-the-Better (HB) characteristic

Here,

y = Average of observed values,

S_y^2 =Variance of y,

N = Number of observations,

y= Observed data

2.2 TOPSIS

TOPSIS (*Technique for Order Preference by Similarity to Ideal Solution*) method is very popular and widely being used as a multi-attribute decision making (MADM) methodology proposed by **Hwang and Yoon (1981)**. The basic concept of this method is that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from negative ideal (anti-ideal) solution. Positive ideal solution is a solution that maximizes the benefit criteria and minimizes cost criteria; whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria. **Tong and Su (1997)** highlighted that Taguchi's quadratic loss function and the indifference curve in the TOPSIS method having similar features. The Taguchi method deals with a one-dimensional problem, whereas TOPSIS method handles multi-dimensional problems. As a result, the relative closeness computed in TOPSIS can be used as a performance measurement index for optimizing multi-response problems in the Taguchi method. **Liao, 2003; Wang and He (2008)** also applied TOPSIS for solving multi-response optimization problems. Following are the procedural steps involved in TOPSIS method.

Step 1: This step involves development of initial decision-making matrix. The row of this matrix is allocated to one alternative; each column corresponds to one attribute values for various alternatives. The decision making matrix can be expressed as:

$$\mathbf{D} = \begin{array}{c} A_1 \\ A_2 \\ . \\ A_i \\ . \\ A_m \end{array} \begin{bmatrix} x_{11} & x_{12} & . & x_{1j} & x_{1n} \\ x_{21} & x_{22} & . & x_{2j} & x_{2n} \\ . & . & . & . & . \\ x_{i1} & x_{i2} & . & x_{ij} & . \\ . & . & . & . & . \\ x_{m1} & x_{m2} & . & x_{mj} & x_{mn} \end{bmatrix} \qquad \textbf{(2.4)}$$

Here, A_i $((i=1,2,.......,m)$ represents the possible alternatives; x_j $(j=1,2,........,n)$ represents the attributes relating to alternative performance, $j=1,2,..........,n$ and x_{ij} is the performance of A_i with respect to attribute $X_{j.}$

Step 2: Obtain the normalized decision matrix r_{ij} .This can be represented as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad \textbf{(2.5)}$$

Here, r_{ij} represents the normalized performance of A_i with respect to attribute $X_{j.}$

Step 3: obtain the weighted normalized decision matrix, $\mathbf{V} = \lfloor v_{ij} \rfloor$ can be found as:

$$V = w_j r_{ij} \quad \textbf{(2.6)}$$

Here, $\sum_{j=1}^{n} w_j = 1$

Step 4: Determine the ideal (best) and negative ideal (worst) solutions in this step. The ideal and negative ideal solution can be expressed as:

a) The ideal solution:

$$A^+ = \left\{ \left(\max_i v_{ij} \mid j \in J \right), \left(\min_i v_{ij} \mid j \in J^{'} \middle| i = 1, 2, ..., m \right) \right\} \quad \textbf{(2.7)}$$

$$= \left\{ v_1^+, v_2^+, ..., v_j^+, ...v_n^+ \right\}$$

b) The negative ideal solution:

$$A^- = \left\{ \left(\min_i v_{ij} \mid j \in J \right), \left(\max_i v_{ij} \mid j \in J^{'} \middle| i = 1, 2, ..., m \right) \right\} \quad \textbf{(2.8)}$$

$$= \left\{ v_1^-, v_2^-, ..., v_j^-, ...v_n^- \right\}$$

Here,

$J = \{ j = 1,2,......., n \mid j \}$: Associated with the beneficial attributes

$J^{'} = \{ j = 1,2,......., n \mid j \}$: Associated with non beneficial adverse attributes

Step 5: Determine the distance measures. The separation of each alternative from the ideal solution is given by *n-dimensional Euclidean distance* from the following equations:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)},\ i = 1, 2, \ldots\ldots\ldots, m \qquad \textbf{(2.9)}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)},\ i = 1, 2, \ldots\ldots\ldots, m \qquad \textbf{(2.10)}$$

Step 6: Calculate the relative closeness (also called closeness coefficient, CC) to the ideal solution:

$$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-},\ \ i = 1, 2, \ldots\ldots\ldots, m; 0 \le C_i^+ \le 1 \qquad \textbf{(2.11)}$$

Step 7: Rank the preference order. The alternative with the largest relative closeness is the best choice.

In the present study C_i^+ for each experimental run has been termed as Multi-Performance Characteristic Index (MPCI) which has been optimized by Taguchi method.

2.3 Principal Component Analysis (PCA)

Data preprocessing is the first step in Principal Component Analysis (PCA) which transfers original data sequence to a comparable sequence. PCA is a multivariate statistical approach, which allows the representation of the original database into a new reference system characterized by new variables called principal components (PCs). Each PC has the property of explaining the maximum possible amount of variance obtained in the original dataset. The PCs, which are expressed as linear combinations of the original variables, are orthogonal to each other and can be used for effective representation of the system under investigation, with a lower number of variables in the new system of variables being called scores, while the coefficient of linear combination describes each PCs, i.e. the weight of original variables of each PC. To avoid any influence on the optimization of the machining process from the units used for evaluating the MPCs, normalization of the data required, in order to provide information for determining the optimal levels of process parameters.

The normalization is taken by the following Equations.

1) For Lower-the-Better (LB) criterion

$$\hat{x}_i(k) = \frac{\max_k x_i(k) - x_i(k)}{[\max_k x_i(k)] - \min_k x_i(k)}, \tag{2.12}$$

2) For Higher-the-Better (HB) criterion

$$\hat{x}_i(k) = \frac{x_i - \min_k x_i(k)}{[\max_k x_i(k)] - \min_k x_i(k)}, \tag{2.13}$$

Here, $\hat{x}_i(k)$ denotes the value after normalization for the k_{th} quality characteristic value, $x_i(k)$ is the experimental data of k_{th} quality characteristic during i_{th} experiment.

The obtained data may have a number of variables and there may be some redundancy (correlation) among those variables. To get rid of such correlation, it is possible to reduce a set of observed variables into a smaller set of new variables called principal components. Principal components analysis is a method that reduces data dimensionality by performing a covariance/correlation analysis between factors and linear combination of optimally-weighted observed variables. Factor analysis is used to summarize the data structure in a few dimensions of the data and also explain the dimensions associated with large data variability. An orthogonal rotation simply rotates the axes to give a different perspective. The different methods are *Equimax*, *Varimax*, *Quartimax*, and *Orthomax*. A parameter, gamma is determined during the rotation method. If the method with a low value of gamma is used, the rotation will tend to simplify the rows of the loadings and if the method with a high value of gamma is used the rotation will tend to simplify the columns of the loadings. *Varimax* rotation is used because it maximizes the variance of the squared loadings.

PCA is a way of identifying patterns in the correlated data, and expressing the data in such a way so as to highlight their similarities and dissimilarities/differences. The main advantage of PCA is that once the patterns in data have been identified, the data can be compressed, i.e. by reducing the number of dimensions, without much loss of information. PCA is an efficient statistical technique while studying multi-quality characteristics, those are highly correlated. The PCA allows data which contain information of multi-quality characteristics to be converted into several independent quality indicators. Part of these indicators is then selected to construct a composite quality indicator, which is the representative of multi-quality features of the process output. The methods involved in PCA are discussed below:

1. Getting some data
2. Normalization of data
3. Calculation of covariance/correlation matrix.
4. Interpretation of covariance/correlation matrix.

The normalized data have then been utilized to construct a variance-covariance matrix M, which is illustrated as below:

$$M = \begin{bmatrix} N_{1,1} & N_{1,2} & . & . & . & N_{1,u} \\ N_{2,1} & N_{2,2} & . & . & . & N_{2,p} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ N_{q,1} & N_{q,2} & . & . & . & N_{q,p} \end{bmatrix} \qquad \textbf{(2.14)}$$

Here $N_{k,l} = \dfrac{Cov(Y_{i,k}^{*}, Y_{i,l}^{*})}{\sqrt{Var(Y_{i,k}^{*})Var(Y_{i,l}^{*})}}$ **(2.15)**

In which u stands for the number of quality characteristics and p stands for the number of experimental runs. Then, eigenvectors and Eigen values of matrix M can be computed, which are denoted by $\overline{V}_j$ and λ_j respectively.

In PCA the eigenvector $\overline{V}_j$ represents the weighting factor of j number of quality characteristics of the jth principal component. For example, if Q_j represents the jth quality characteristic, the jth principal component ψ_j can be treated as a quality indicator with the required quality characteristic.

$$\psi_j = V_{1j}Q_1 + V_{2j}Q_2 + \ldots\ldots\ldots\ldots\ldots\ldots\ldots + V_{jj}Q_j = \overline{V}_j^{'}\overline{Q} \quad \textbf{(2.16)}$$

It is to be noted that every principal component ψ_j represents a certain degree of explanation of the variation of quality characteristics, namely the accountability proportion (AP). When several principal components are accumulated, it increases the accountability proportion of quality characteristics. This is denoted as cumulative accountability proportion (CAP). The composite principal component ψ may be defined as the sum/ linear combination of principal components with their individual Eigen values. Thus, the composite principal component represents the overall quality indicator as shown below:

$$\psi = \sum_{j=1}^{k} \psi_j \quad \textbf{(2.17)}$$

If a quality characteristic Q_j strongly dominates in the jth principal component, this principal component becomes the major indicator of such a quality characteristic. It should be noted that one quality indicator may often represent all the multi-quality characteristics. Selection of individual principal components (ψ_j), those to be included in the composite quality indicator ψ, depends on their individual accountability proportion. Application of PCA has been found in the work carried out by **(Su and Tong, 1997; Datta et al., 2009b; Routara et al., 2010)**.

2.4 Utility Theory

There are always more than one quality responses (or output characteristics) in product/ process design and it is often required to choose an optimum parameter combination for these responses simultaneously. Taguchi method, as a cost-effective method for off-line quality control, has been widely employed by quality engineering to deal with single-response problem, but fails to solve multi-objective optimization problem. In order to overcome this, utility theory **(Walia et al., 2006; Datta et al., 2006)** have been applied by previous investigators in combination with Taguchi method. The methodological basis for utility approach is to transform the estimated response of each quality characteristic into a common index. It is the measure of effectiveness of an attribute (or quality characteristics) and there are attributes evaluating the outcome space, then the joint utility function can be expressed as:

$$U(X_{1,}\ X_2, \ldots\ldots\ldots\ldots\ldots, X_n) = f\,(U_1(X_1), U_2(X_2), \ldots\ldots\ldots\ldots\ldots, U_n(X_n)) \tag{2.18}$$

The overall utility function is the sum of individual utilities if the attributes are independent, and is given as follows:

$$U(X_{1,}\ X_2, \ldots\ldots\ldots\ldots\ldots, X_n) = \sum_{i=1}^{n} U_i(X_i) \tag{2.19}$$

The overall utility function after assigning weights to the attributes can be expressed as:

$$U(X_{1,}\ X_2, \ldots\ldots\ldots\ldots\ldots, X_n) = \sum_{i=1}^{n} W_i \otimes U_i(X_i) \tag{2.20}$$

The preference number can be expressed on a logarithmic scale as follows:

$$P_i = A \times \log\left(\frac{X_i}{X_i^{'}}\right) \tag{2.21}$$

Here,

X_i is the value of any quality characteristic or attribute i

$X_i^{'}$ is just acceptable value of quality characteristic or attribute i and A is a constant. The value A can be found by the condition that if $X_i = X^*$ (where X^* is the optimal or best value), then $P_i = 9$. Therefore,

$$A = \frac{9}{\log \frac{X^*}{X_i^{'}}} \tag{2.22}$$

The overall utility can be expressed as follows:

$$U = \sum_{i=1}^{n} W_i \otimes P_i \tag{2.23}$$

Subject to the condition:

$$\sum_{i=1}^{n} W_i = 1 \tag{2.24}$$

Overall utility index generally servers as the single objective function for optimization. Among various quality characteristics types, viz. Lower-the-Better (LB), Higher-the-Better (HB), and Nominal-the-Best (NB) suggested by Taguchi, the utility function would be Higher-the-Better type. Therefore, if the quality function is maximized, the quality characteristics considered for its evaluation would automatically be optimized (maximized or minimized as the case may be).

2.5 Desirability Function

Desirability function approach was first proposed by **Derringer and Suich (1980)**. In desirability function approach, individual responses are transformed to corresponding desirability values. Desirability value depends on acceptable tolerance range as well as target of the response. Unity is assigned, as the response reaches its target value, which is the most desired situation. If the value of the response falls beyond the prescribed tolerance rage, which is not desired, its desirability value is assumed as zero. Therefore, desirability value may vary from zero to unity.

There are three different types of desirability characteristics.

1. Higher-the-Better (HB)
2. Lower-the-Better (LB)
3. Nominal-the-Best (NB)

Higher-the-Better (HB)

Desirability function corresponding to Higher-the-Better (HB) criterion has been shown in **Fig. 2.5**. The value of $\hat{y}$ is expected to be the high. When $\hat{y}$ exceeds a particular criteria value, according to the requirement, the desirability value d_i equals to 1; if $\hat{y}$ is less than a particular criteria value, i.e. less than the acceptable limit, the desirability value equals to 0. The desirability function of the Higher-the-Better (HB) criterion can be written in the form as given in **Eqs (2.25-2.27)**. Here $y_{\min}$ denotes the lower tolerance limit of $\hat{y}$, the $y_{\max}$ represents the upper tolerance limit of $\hat{y}$ and r represents the desirability function index, which is to be assigned previously according to the consideration of the decision-maker.

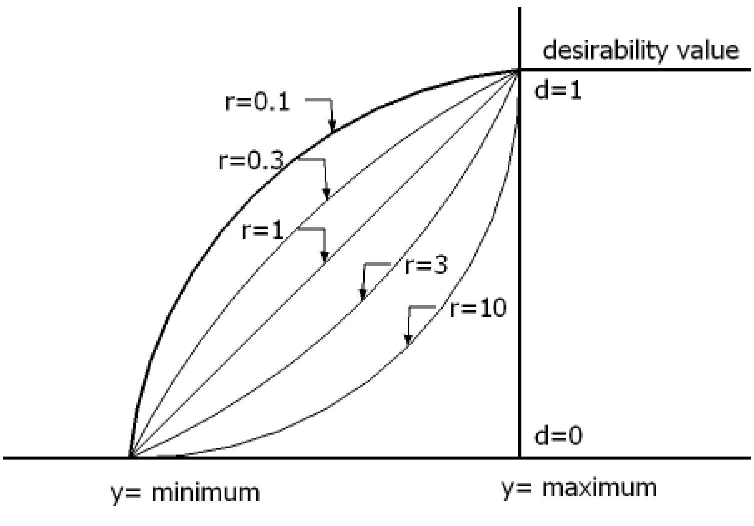


Figure 2.5: Desirability function (Higher-the-Better)

$$\hat{y} \le y_{\min},\ d_i = 0 \tag{2.25}$$

$$y_{\min} \le \hat{y} \le y_{\max},$$

$$d_i = \left(\frac{\hat{y} - y_{\min}}{y_{\max} - y_{\min}} \right)^r \tag{2.26}$$

$$\hat{y} \ge y_{\max},\ d_i = 1 \tag{2.27}$$

Lower-the-Better (LB)

The desirability function corresponding to Lower-the-Better (LB) criterion has been shown in **Fig. 2.6**. The value of $\hat{y}$ is expected to be as less as possible. When $\hat{y}$ is less than a particular criteria value, the desirability value d_i equals to 1; if $\hat{y}$ exceeds a particular criteria value, the desirability value equals to 0. If d_i varies within the range (0, 1). The desirability function of the Lower-the-Better (LB) criterion can be written as below in **Eqs. (2.28-2.30)**. Here $y_{\min}$ denotes the lower tolerance limit of $\hat{y}$, the $y_{\max}$ represents the upper tolerance limit of $\hat{y}$ and r represents the desirability function index, which is to be assigned previously according to the consideration of the decision-maker.

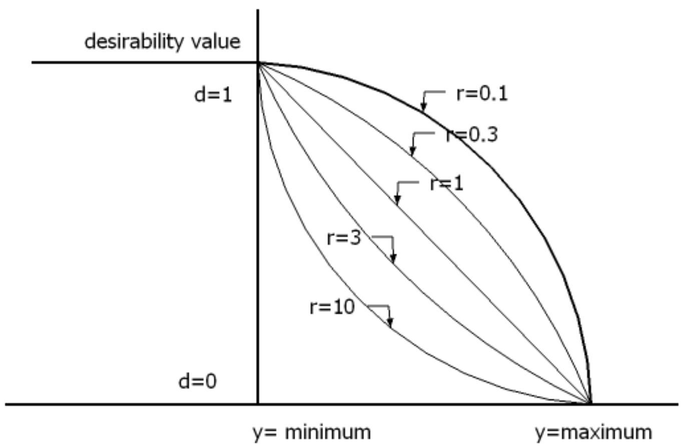


Figure 2.6: Desirability function (Lower-the-Better)

$$\hat{y} \le y_{\min},\ d_i = 1 \tag{2.28}$$

$$y_{\min} \le \hat{y} \le y_{\max},$$

$$d_i = \left(\frac{\hat{y} - y_{\max}}{y_{\min} - y_{\max}} \right)^r \tag{2.29}$$

$$\hat{y} \ge y_{\max},\ d_i = 0 \tag{2.30}$$

Nominal-the-Best (NB)

The values of $\hat{y}$ are required to achieve a particular target T as shown in **Fig. 2.7**. When $\hat{y}$ equals to T, the desirability value equals to 1; if the departure of $\hat{y}$ exceeds a particular range from the target, the desirability value equals to 0, and such situation represents the worst case. The desirability function for the Nominal-the-Best (NB) can be written as given in **Eqs. (2.31-2.32)**.

$$y_{\min} \le \hat{y} \le T,$$

$$d_i = \left(\frac{\hat{y} - y_{\min}}{T - y_{\min}} \right)^r \tag{2.31}$$

$$T \le \hat{y} \le y_{\max},$$

$$d_i = \left(\frac{\hat{y} - y_{\max}}{T - y_{\max}} \right)^r \tag{2.32}$$

Here,

$y_{\max}$ and $y_{\min}$ represent the upper/lower tolerance limits of $\hat{y}$ and r represent the desirability function index.

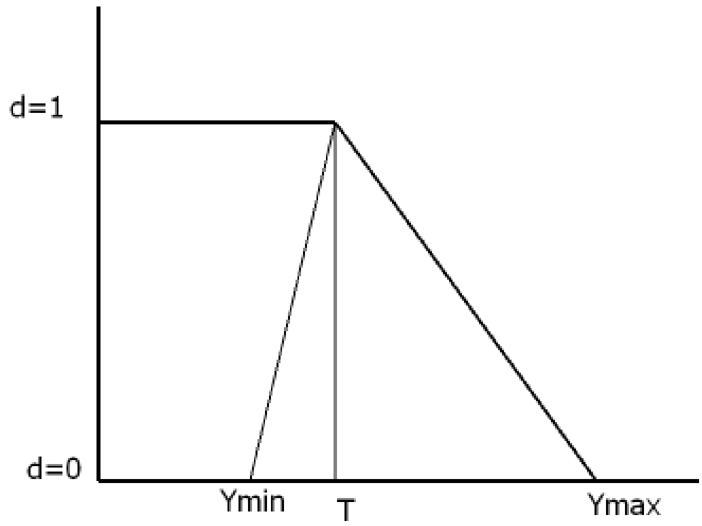


Figure 2.7: Desirability function (Nominal-the-Best)

The individual desirability values are then accumulated to calculate the overall desirability D_O, using **Eq. 2.33**. Here D_O is the overall desirability value, d_i is the individual desirability value of i_{th} quality characteristic and n is the total number of responses. The value w_i is the weight for i_{th} quality attribute. Sum of all attribute weights should be equal to 1.

$$D_0 = \left(d_1^{w_1}.d_2^{w_2}.......d_n^{w_n}\right)^{1/\sum w_i} \qquad \textbf{(2.33)}$$

2.6 Fuzzy Inference System (FIS)

Fuzzy logic is a mathematical theory of inexact reasoning, which allows the human reasoning process to be modeled in linguistic terms **(Yager and Filev, 1999)**. It is highly suitable for defining the relationship between system input and desired outputs. Fuzzy controllers and fuzzy reasoning have found particular applications in very complex industrial systems which cannot be modeled precisely even under a variety of assumption and approximations. A fuzzy rule based system consists of four parts:

1. **Fuzzification Module:** Transforms the system inputs, which are crisp numbers, into fuzzy sets. This is done by applying a fuzzification function.
2. **Knowledge Base:** Stores IF-THEN rules provided by experts.
3. **Inference Engine:** Simulates the human reasoning process by making fuzzy inference on the inputs and IF-THEN rules.
4. **Defuzzification Module:** Transforms the fuzzy set obtained by the inference engine into a crisp value.

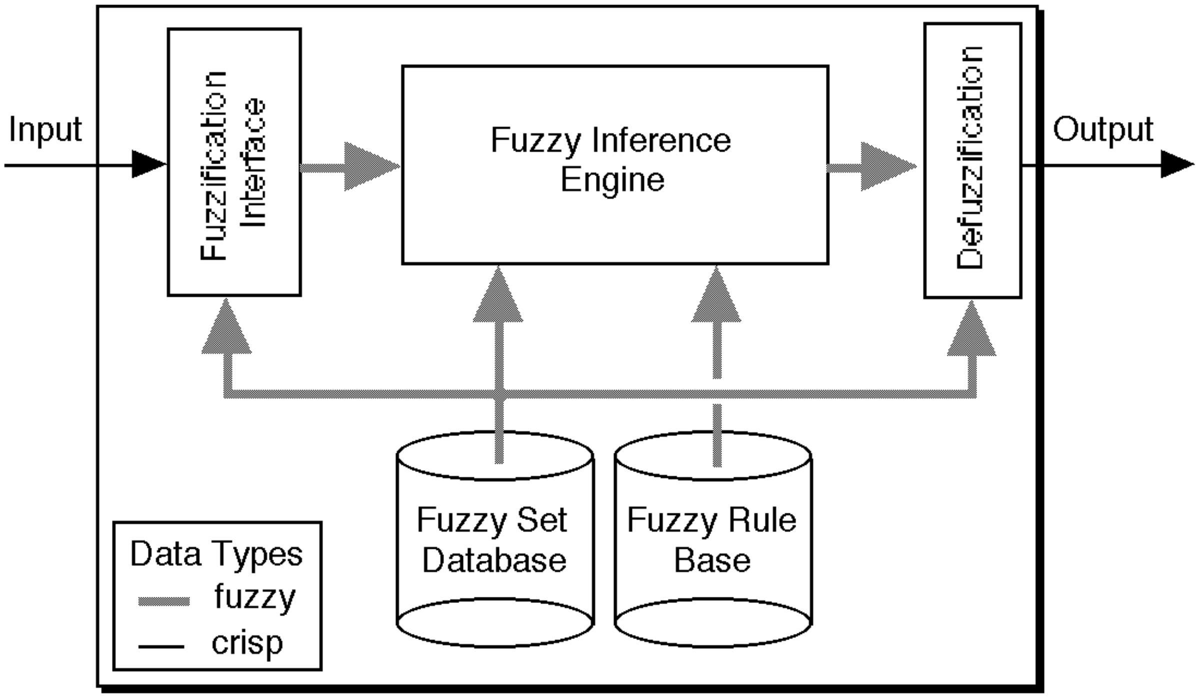
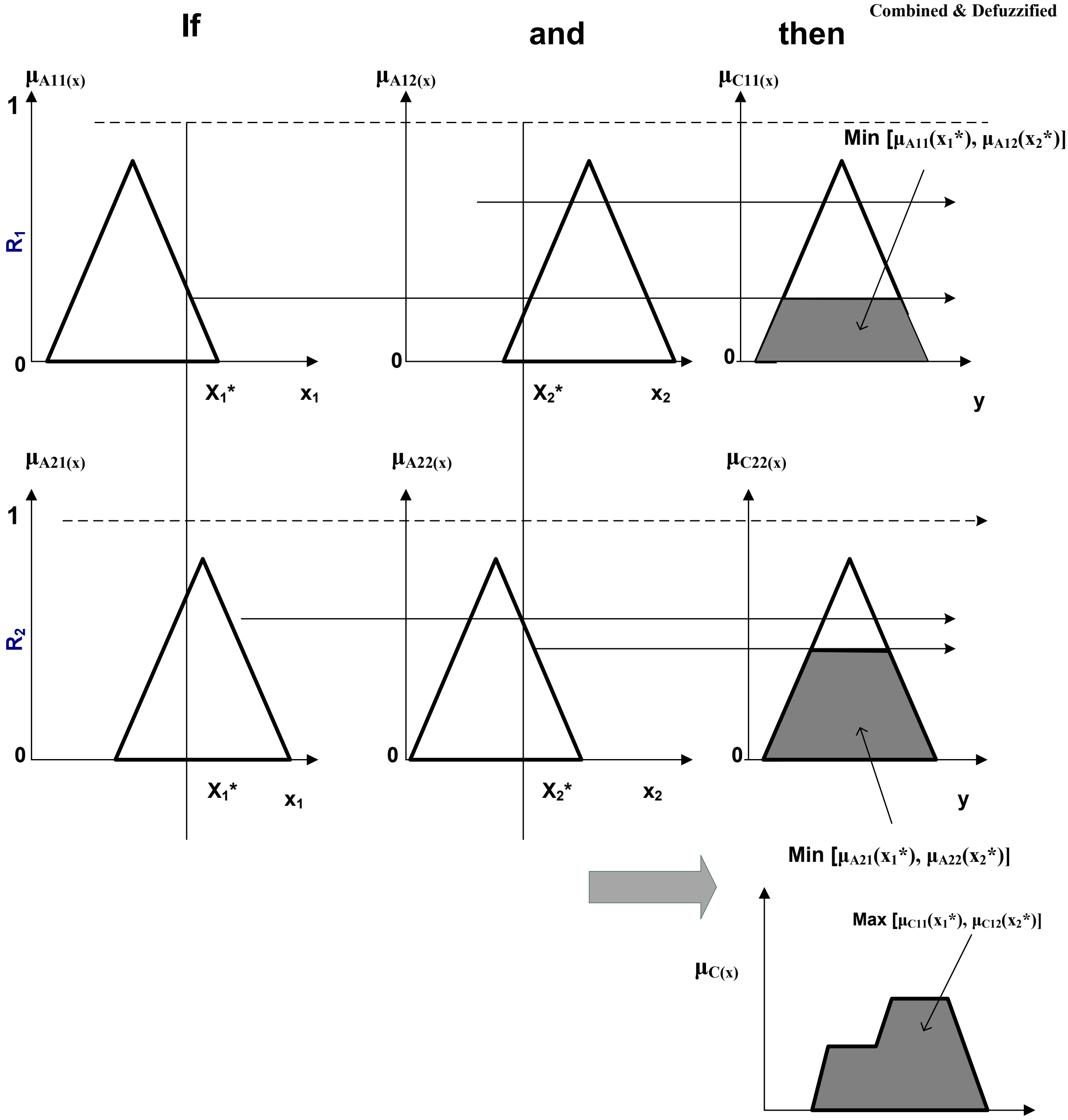


Figure 2.8: Basic configuration of a fuzzy inference system (FIS)

Fuzzy values are determined by the membership functions, which define the degree of membership of an object in a fuzzy set **(Cox, 1992)**. However, so far there has been no standard method of choosing the proper shape of the membership functions for the fuzzy set of control variables. Trial and error methods are usually employed. On the basis of fuzzy rules, the Mamdani implication method **(Mendel, 1995; Sivarao et al., 2009)** is employed in this study for fuzzy inference reasoning.



Mamdani Fuzzy Logic Reasoning Process

Figure 2.9: Mamdani implication method with fuzzy controller operations
(Fang et al., 2008)

To obtain a rule,

$$R_i : if\ x_1\ is\ A_{i1}, x_2\ is\ A_{i2}, and\ x_s\ is\ A_{iM}$$

$$Then, y_i\ is\ C_i, \qquad \textbf{(2.34)}$$

Here M is the total number of fuzzy rules. $x_j\ (j=1,2,,........,s)$ are the input variables, y_i are the output variables and $A_{ij}\ and C_i$ are fuzzy sets modeled by the membership functions $\mu_{Aij}(x_j)$ and $\mu_{Ci}(y_i)$, respectively. Based on the Mamdani implication method of inference reasoning for a set of disjunctive rules, the aggregated output for the M rules is

$$\mu_{Ci}(y_j) = \max\{\min[\mu_{Ai1}(x_1), \mu_{Ai2}(x_2),......, \mu_{Ais}(x_s)]\}, \qquad i = 1,2,........, M \qquad \textbf{(2.35)}$$

Elements of a Fuzzy Inference System (FIS) have been shown in **Fig. 2.8**. The above equation is illustrated in **Fig. 2.9**. The graph represents the fuzzy reasoning process for two rules, R_1 and R_2, with two input variables which are triangle shaped membership functions. Using a defuzzification method, fuzzy values can be combined into one single crisp output value. The centre of gravity, one of the most popular methods for defuzzifying fuzzy output functions, is employed in this study. The formula to find the centroid of the combined outputs $\hat{y}_i$ is given by:

$$\hat{y}_i = \frac{\int y_i \mu_{ci}(y_i)dy}{\int \mu_{ci}(y_i)dy} \qquad \textbf{(2.36)}$$

2.7 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-fuzzy inference system is a fuzzy inference system implemented in the framework of an adaptive neural network. By using a hybrid learning procedure, ANFIS can construct an input-output mapping based on both human-knowledge as fuzzy if-then rules and stipulated input-output data pairs for neural networks training. ANFIS architecture has been shown in **Fig. 2.10**. Five network layers are used by ANFIS to perform the following fuzzy inference steps: (i) Input Fuzzification, (ii) Fuzzy Set Database Construction, (iii) Fuzzy Rule Base Construction, then (iv) Decision-Making and (v) Output Defuzzification. Learning or training phase of a neural network is a process to determine parameter values to sufficiently feed the training data. The basic learning rule method is the back propagation (BP) method, which seeks to minimize errors, usually sum of squared differences between network's outputs and desired outputs. Generally, the model performance is checked by the means of distinct test data, and relatively good mapping is expected in the testing phase. Considering a 1^{st} Takagi, Sugeno and Kang (TSK) fuzzy interface system, a fuzzy model consists of two rules **(Sugeno and Kang, 1988)**.

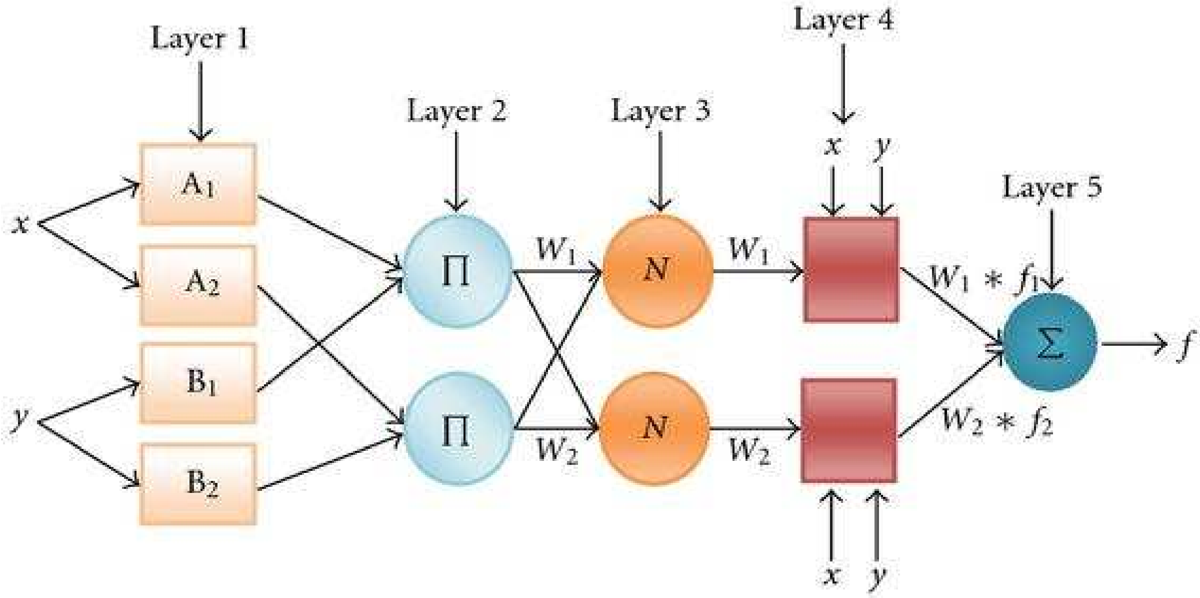


Figure: 2.10 ANFIS architecture

ANFIS is more powerful than the simple fuzzy logic algorithm and neural networks. It provides a method for fuzzy modeling to learn information about the data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. From ANFIS architecture **(Fig. 2.10)**, it is observed that the given values of the of premise parameters, the overall output function can be expressed as a linear combination of the consequent parameters. Based on this observation a hybrid learning rule is employed here, which combines a gradient decent and the least squares method to determine a feasible of antecedent and consequent parameters **(Jang1991; Jang 1993)**.

ANFIS on-line identification of a characteristic feature starts by obtaining the data set (input-output data pairs) and dividing it into training and checking or validating data sets. The training data set is used to find the initial premise parameters for the fuzzy membership functions by equally spacing each membership function. The values of the premise parameters are fixed, so the overall on-line predicted characteristic feature under consideration can be expressed as a linear combination of consequent parameters.

The Sugeno fuzzy model **(Jang and Sun, 1995)** describes the ANFIS architecture and its learning algorithm. The fuzzy inference system has two inputs m and n and one output f . For a first-order Sugeno fuzzy model, a typical rule set with two fuzzy IF–THEN rules can be expressed as:

Rule 1: $if\ (m\ is\ A_1)\ and\ (n\ is\ B_1)\ then\ f_1 = p_1 m + q_1 n + r_1$ **(2.37)**

Rule 2: $if\ (m\ is\ A_2)\ and\ (n\ is\ B_2)\ then\ f_2 = p_2 m + q_2 n + r_2$ **(2.38)**

Here, $p_1, p_2, q_1, q_2, r_1\ and\ r_2$ are linear parameters, and $A_1, A_2, B_1\ and\ B_2$ are non linear parameters.

The corresponding equivalent ANFIS architecture has been shown in **Fig. 2.10**. The entire system architecture consists of five layers, namely, a fuzzy layer, a product layer, a normalized layer, a defuzzy layer and a total output layer. The following section discussed the relationship between the output and input of each layer in the ANFIS.

Layer 1 is the fuzzy layer, in which m and n are the input of nodes $A_1, A_2, B_1\ and\ B_2$ respectively. $A_1, A_2, B_1\ and\ B_2$ are the linguistic labels used in the fuzzy theory for dividing the membership functions. The membership relationship between the output and input functions of this layer can be expressed as:

$$O_{1,i} = \mu_{Ai}(m) \qquad (i=1,2)$$
$$O_{1,j} = \mu_{Bj}(n) \qquad (j=1,2) \qquad \textbf{(2.39)}$$

Here $O_{1,i}$ and $O_{1,j}$ denote the output functions and μ_{Ai} and μ_{Bj} denote the membership functions.

Layer 2 is the product layer that consists of two nodes labeled as Π. The output w_1 and w_2 are the weight functions of the next layer. The output of this layer is the product of the input signal, which is defined as follows:

$$O_{2,i} = w_i = \mu_{Ai}(m)\mu_{Bi}(n) \qquad (i=1,2) \qquad \textbf{(2.40)}$$

Here, $O_{2,i}$ denotes the output of Layer 2.

The third layer is the normalized layer, whose nodes are labeled N. Its function is to normalize the weight function in the following process:

$$O_{3,i} = \overline{w} = \frac{w_i}{w_1 + w_2} \qquad (i=1,2) \qquad \textbf{(2.41)}$$

Here, $O_{3,i}$ denotes the layer 3 output.

The fourth layer is the defuzzy layer, whose nodes are adaptive. The output equation is $\overline{w}(pm+qn+r)$, where $p_i, q_i \; and \; r_i$ denote the linear parameters or so-called consequent parameters of the node. The defuzzy relationship between the input and output of this layer can be de fined as:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i m + q_i n + r_i) \qquad (i=1,2) \qquad \textbf{(2.42)}$$

Here, $O_{4,i}$ denotes the Layer 4 output.

The fifth layer is the total output layer, whose node is labeled as Σ. The output of this layer is the total of the input signals, which represents the tool-state (normal or failure) detection result. The results can be written as:

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (i = 1, 2) \tag{2.43}$$

Here, $O_{5,i}$ denotes the Layer 5 output.

Chapter 3
Application of TOPSIS based Taguchi Method

3.1 Coverage

Quality and productivity are the two major parameters of concern for every manufacturing or production unit in order to achieve high quality product towards fulfillment of the need and satisfaction of the customers in an economic way. In this globalization era, there are more than one product quality assessment factors that lead to competition in the marketplace. So the main goal is to find the optimum solution to satisfy customers' multiple needs of the product performance in an economic cost.

Glass fiber reinforced polymer (GFRP) comprises high strength to weight ratio, toughness, excellent corrosion and thermal resistance. Due to its excellent properties over other engineering materials GFRP composite is being applied in defence, aerospace engineering, civil engineering and automobile engineering as well. Due to widespread upcoming applications of GFRP composites; machining and machinability aspects of composites have become the major concern of the industrialists as well as academicians. During production process, the main concern is to produce a specified surface texture because it depends on the various input parameters selected during operation. A small change in the machining parameters seemed to impose significant effect on the surface produced. Therefore, optimization of machining parameters is the major issue to enhance product quality as well as overall performance of the said process.

In this chapter, TOPSIS technique has been integrated with Taguchi's philosophy towards solving multi-objective optimization problem in machining of composites as a case study. The following paragraph describes some of the important investigations carried out by pioneers towards successful implementation of TOPSIS method.

Hwang and Yoon (1981) classified the multi-attribute decision making (MADM) problem on the basis of the type of information of the decision maker and the salient features of the information. The authors described TOPSIS as the suitable method due to information given in cardinal preferences of the attributes. **Lan (2009)** proposed a multi objective integration technique using orthogonal array and TOPSIS technique to optimize the precision CNC turning conditions. The optimum multi-objective cutting parameters were achieved by analysis of factor responses in the Taguchi experiment. **Yang and Chou (2005)** assumed the control factors as a discrete value by which Taguchi quality loss function were adapted to solve the mean and variance effects. Further TOPSIS method was used to find the replaced objective function for the multiple responses and also assessed the distance from the positive and negative ideal solution of each alternative. **Angun et al. (2003)** solved the multi response problem by choosing one response as objective and remaining as constraints. The search direction was scaled and project estimated steepest-descent direction called the estimated affine scaling search direction. **Tong and Su (1997)** adopted a MADM method a technique for order preference by similarity to ideal solution (TOPSIS) to optimize the multi-response robust design problem. They considered the sampling variability of each response by the Taguchi quality loss function. **Wang and He (2007)** reported that in conventional TOPSIS method, responses were usually transformed into quality loss, and then normalized by the largest quality loss which was not suitable for Nominal-the-Best (NB) problem. So, modified method was proposed based on the TOPSIS and made an improvement to adapt a nominal the best responses. **Liu (2011)** provided an extended method of

TOPSIS in which attributes values and priority weight took the form of generalized interval valued trapezoidal fuzzy number (GIVTFN).

Literature survey (described in **Chapter 1**) reveals that traditional methods are very straightforward (consisting of a number of assumptions) and not free from limitations. It is seemed that TOPSIS method adapted from Multi-Criteria Decision Making (MCDM) combined with Taguchi method has not been applied before in the field of composite machining. Moreover, most of the studies concentrated on optimizing average surface roughness (R_a) only. But there exist a number of surface roughness parameters of statistical importance which need to be investigated in detail. In this context, the study explores application of TOPSIS based MCDM combined with Taguchi method **(Yang and Tang, 1998)** for parametric optimization in machining of glass fiber reinforced polyester composites while considering multiple surface roughness characteristics of the machined work piece. The detailed description of the methodology followed by application feasibility has been described in later part.

3.2 Experimentation

The multi-criteria based optimization of the machining (turning) process for GFRP composites is primarily concentrated towards optimizing the process conditions to obtain the least extent of a set of surface roughness characteristics of the machinated surface. There are multiple surface roughness characteristics (R_a, R_z, R_t, R_{sm}, R_{ku}, R_{z1max} etc.) of statistical importance. Different surface roughness characteristics are used in different convention systems in different countries. The objective of the thesis is to find out a practical optimization problem consisting of mutually correlated response features (output measure). Aforesaid multiple roughness features are correlated to each other and greatly influenced by the process control parameters. In order to achieve high surface finish, all these parameters need to be optimized (minimized) simultaneously. It is true that in general, the surface roughness of a machined surface is simply evaluated by finding out the corresponding R_a value in almost all topical literature. However, the following are the references **(Davim and Mata, 2005; Palanikumar et al., 2008; Palanikumar, 2008a)** in which pioneer researchers pointed out the importance of simultaneous consideration of multiple roughness features. Motivated by this, the study has been planned to consider correlated multiple surface roughness characteristics in the list of objective functions for the said composite machining.

The present study has been done through the following plan of experiments.

A. Checking and preparing the centre lathe ready for performing the machining operation.
B. Cutting GFRP bars and performing initial turning operation in lathe to get desired dimension ($\phi 50\times 150$) of the work pieces.
C. Performing straight turning operation on specimens in various cutting environments involving various combinations of process control parameters like spindle speed, feed and depth of cut.
D. Measuring surface roughness parameters with the help of a portable stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+, UK).

Glass fiber (E-glass-R099 1200 P556) reinforced Polyester composite has been selected as work piece material. The specifications of the work piece material have been shown in **Table 3.1**. The ISO specification of the tool holder used for the turning operation is a WIDAX tool holder PC LNR 2020 K12 and the tool insert used for the study are carbide K-20, (CNMA 120408).

In the present study, spindle speed (N, RPM), feed rate (f, mm/min) and depth of cut (d, mm), have been selected as design factors while other parameters have been assumed to be constant over the experimental domain. The process variables (design factors) with their values at different levels have been listed in **Table 3.2**. It is known that the selection of the values of the variables is limited by the capacity of the machine used in the experimentation as well as the recommended specifications for different work piece and tool material combinations. Therefore, three levels have been selected for each of the aforesaid three factors. In the present investigation, Taguchi's L_9 orthogonal array (OA) design (without factorial interaction) has been considered for experimentation **(Table 3.3)**. The machine used for turning is PINACHO lathe (specifications have been included at the end of this chapter). The surface roughness parameters have been measured using the stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+). The values of measured roughness parameters: (average of two trials) R_q, R_a, R_t, R_{ku}, R_z, R_{sm} have been shown in **Table 3.4** with pictorial representations of surface profile shown in at the end of this thesis (**Appendix 1)**. The definitions of aforesaid surface roughness parameters along with MRR have also been included at the end of this thesis (**Appendix 2)**.

It is widely accepted in most of the manufacturing process optimization that experimental designs based on Taguchi's Orthogonal Array (OA) is used a starting point since it allows the identification of the interaction effects of independent variables on the responses. A full factorial design of experiment represents all parametric combinations. As number of factors and their levels of variation increase; the total number of experimental run in full-factorial design of experiment exponentially increases. This results in consumption of excessive time and cost. Taguchi philosophy adopts OA to reduce experimentation time and cost. Without conducting large set of experiments; only a limited number of experiments are required for reliable prediction of the optimal. Therefore, adaptation of L_9 OA instead of full-factorial design of experiment is fully justified.

3.3 Numerical Illustrations

The methodology adopted for solution of multi-response optimization problem has been summarized in a block diagram shown at the end of this thesis **(Appendix 3)**. Six output responses related to various surface roughness parameters has been taken as criteria attributes with nine alternatives (process environments). Taguchi's loss function in the form of S/N ratio has been calculated to account for the mean and variability of each response. For all the surface roughness parameters, S/N ratio has been calculated based on Lower-the-Better (LB) criteria **(Eq. 3.1)**.

$$S/N = -10\log\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \tag{3.1}$$

Here, n is the number of measurements, and y_i the measured i_{th} characteristic value i.e. i_{th} quality indicator.

Calculated S/N ratios have been shown in **Table 3.5**. The normalized S/N ratios have been computed using **Eq. 2.5** of **Chapter 2** and shown in **Table 3.6**.

The next step is to calculate the weight of each attributes by the Standard Deviation Method (SDM) to calculate the weighted normalized rating using **Eq. 3.2**. The calculated weighted normalized S/N ratio values are shown in **Table 3.7**.

The standard deviation method calculates objective weights of the attributes **(Eq. 3.2)**.

$$w_j = \sigma_j / \sum_{k=1}^{M} \sigma_k \tag{3.2}$$

Here, σ_j is the standard deviation of the normalized vector r_{ij} .

The standard deviation method calculates the objective weights of the attributes without giving any consideration to the preferences of the decision maker. The set of factor weight for each surface roughness is w_1 = 0.204213, w_2 = 0.104796, w_3 = 0.199887, w_4 = 0.100424, w_5 = 0.141389, w_6 = 0.249292. The next step is to calculate the ideal (best) and negative ideal (worst) solution i.e. A^+ and A^- (using **Eqs. 2.7-2.8** of **Chapter 2**) and shown in **Table 3.8**. The distance measures i.e. S_i^+, S_i^- (separation distance of each alternative from the ideal one) have been determined by using (**Eqs. 2.9-2.10** of **Chapter 2**). Then calculated distance measures have been shown in **Table 3.9**. Finally, the similarity to ideal solution for each scenario of alternative C_i^+ has been obtained by **Eq. 2.11** of **Chapter 2** (shown in **Table 3.10**). This C_i^+ has been treated as MPCI of the surrogate responses for the proposed multi-response simulation-optimization problem. The alternative with the largest relative closeness is said to be the best choice and made in descending order according to the preference value. The best preference has been determined by optimizing (maximizing) MPCI in Taguchi method. **Fig. 3.1** represents optimal parametric combination (N_3 f_2 d_3) evaluated from mean S/N ratio plot for MPCI. Optimal result has been validated by satisfactory confirmatory test. Predicted value of S/N ratio of MPCI becomes -1.55809 (highest among all entries of MPCIs SN ratio in **Table 3.10**). In confirmatory experiment the value came -1.4367. So, quality has improved using the said optimal setting. **Table 3.11** represents mean values table of S/N ratios of MPCIs. The degree of influence of various factors on MPCI can be estimated from this analysis. It shows that feed rate is the most significant factor on influencing MPCIs following with depth of cut and spindle speed.

3.4 Concluding Remarks

This chapter presents an integrated optimization philosophy using TOPSIS concept combined with Taguchi method for optimizing multiple surface roughness parameters optimization in machining of GFRP composites. The study illustrates the effectiveness of the proposed method as well. The analysis in this chapter exposes that Taguchi's quadratic loss function and TOPSIS concept can be efficiently integrated towards a flexible compatible multi-response optimization methodology. The traditional Taguchi method deals with one dimensional problem (single response), while TOPSIS is capable of dealing with multi dimensional problem (multiple criteria attribute). By exploring TOPSIS concept multiple criterions can be logically aggregated to convert a single performance index (MPCI). MPCI can easily be optimized to determine the optimal process environment which facilitates in mass production and consequently product quality improvement.

However, the procedure reported in the preceding sections is not free from limitations. The drawbacks have been enlisted herewith.

1. In this procedure response correlation has not been considered.
2. Individual response weight computed from statistical analysis of experimental data (standard deviation) does not provide accurate degree of response importance in reality. Also it depends on the type of data gathered through experiments.

In order to bypass uncertainty in appropriate assignment of response weights; next chapter explores the concept of fuzzy logic followed by development and subsequent execution of a Fuzzy Inference System (FIS) in order to aggregate multiple performance characteristics (output responses) into a single performance measure. This equivalent unique performance measure has been optimized (maximized) by Taguchi method.

Table 3.1 Specifications of work material

Resin used	Polyester resin
Fiber orientation	Random
Method of preparation	Hand molding method
Composition	75:25 (Resin: Fiber)
Weight percentage of hardener	5%
Density	2 gm/cm^3

Table 3.2 Process parameters and domain of experiment

Process parameters	*Notation*	*Unit*	*Level 1*	*Level 2*	*Level 3*
Cutting speed	N	RPM	360	530	860
Feed rate	f	mm/rev	0.083	0.166	0.331
Depth of cut	d	mm	3	4	5

Table 3.3 Design of experiment: L_9 orthogonal array (factors at coded form)

Sl. No.	*N*	*f*	*d*
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

Table 3.4 Experimental data: multiple surface roughness parameters

Sl. No. (Alternatives)	*Criteria attributes*					
	R_q *(µm)*	R_t *(µm)*	R_{ku}	R_z *(µm)*	R_{sm} *(mm)*	R_a *(µm)*
1	4.140	24.25	2.990	18.60	0.10065	3.375
2	5.735	36.50	3.995	25.75	0.13300	4.585
3	4.015	25.60	4.350	18.45	0.10205	3.190
4	3.430	21.45	4.930	16.05	0.19400	2.685
5	4.580	28.10	5.330	20.55	0.09605	3.560
6	4.650	28.95	3.565	20.75	0.12550	3.785
7	5.595	35.40	3.490	25.45	0.11450	4.550
8	5.615	39.45	5.215	24.85	0.11450	4.540
9	3.180	19.40	4.835	14.05	0.11400	2.515

Table 3.5 Calculated S/N ratios (all responses) in all experimental arrangements

Sl. No.	*S/N Ratio*					
	R_q	R_t	R_{ku}	R_z	R_{sm}	R_a
1	-12.3400	-27.6942	-9.5134	-25.3903	19.9437	-10.5655
2	-15.1707	-31.2459	-12.0303	-28.2155	17.5230	-13.2268
3	-12.0737	-28.1648	-12.7698	-25.3199	19.8237	-10.0758
4	-10.7059	-26.6285	-13.8569	-24.1095	14.2440	-8.5789
5	-13.2173	-28.9741	-14.5345	-26.2562	20.3501	-11.0290
6	-13.3491	-29.2330	-11.0412	-26.3404	18.0271	-11.5613
7	-14.9560	-30.9801	-10.8565	-28.1138	18.8239	-13.1602
8	-14.9870	-31.9209	-14.3451	-27.9065	18.8239	-13.1411
9	-10.0485	-25.7560	-13.6879	-22.9535	18.8619	-8.0108

Table 3.6 Calculated normalized S/N ratio values

Sl. No.	*Normalized S/N Ratio*					
	R_q	R_t	R_{ku}	R_z	R_{sm}	R_a
1	-0.31395	-0.31806	-0.2511821	-0.32397	0.35795527	-0.31472
2	-0.38596	-0.35885	-0.3176358	-0.36001	0.31450785	-0.39399
3	-0.30717	-0.32346	-0.3371608	-0.32307	0.35580148	-0.30013
4	-0.27237	-0.30582	-0.3658635	-0.30762	0.25565542	-0.25554
5	-0.33627	-0.33276	-0.3837541	-0.33501	0.36524946	-0.32852
6	-0.33962	-0.33573	-0.2915206	-0.33609	0.32355558	-0.34438
7	-0.3805	-0.35579	-0.286644	-0.35872	0.33785678	-0.392
8	-0.38129	-0.3666	-0.3787534	-0.35607	0.33785678	-0.39144
9	-0.25565	-0.2958	-0.3614014	-0.29287	0.33853882	-0.23862

Table 3.7 Weighted normalized S/N ratio values

Sl. No.	*Weighted Normalized S/N Ratio*					
	R_q	R_t	R_{ku}	R_z	R_{sm}	R_a
1	-0.06411	-0.03333	-0.05021	-0.03253	0.050611	-0.07846
2	-0.07882	-0.03761	-0.06349	-0.03615	0.044468	-0.09822
3	-0.06273	-0.0339	-0.06739	-0.03244	0.050306	-0.07482
4	-0.05562	-0.03205	-0.07313	-0.03089	0.036147	-0.0637
5	-0.06867	-0.03487	-0.07671	-0.03364	0.051642	-0.0819
6	-0.06935	-0.03518	-0.05827	-0.03375	0.045747	-0.08585
7	-0.0777	-0.03729	-0.0573	-0.03602	0.047769	-0.09772
8	-0.07786	-0.03842	-0.07571	-0.03576	0.047769	-0.09758
9	-0.05221	-0.031	-0.07224	-0.02941	0.047866	-0.05949

Table 3.8 Ideal (best) and negative ideal (worst) solutions for each criterion

Criteria No.	*The ideal (best) A^+*	*The negative ideal (worst) A^-*
1	-0.07882	-0.05221
2	-0.03842	-0.031
3	-0.07671	-0.05021
4	-0.03615	-0.02941
5	0.036147	0.051642
6	-0.09822	-0.05949

Table 3.9 Calculated distance measures

Sl. No.	S_i^+	S_i^-
1	0.039462786	0.022753
2	0.015641724	0.05025
3	0.033585447	0.025695
4	0.042555038	0.02825
5	0.02506716	0.038836
6	0.026289713	0.033536
7	0.022685175	0.047537
8	0.01172835	0.053567
9	0.049657878	0.022351

Table 3.10 The relative closeness of a particular alternative to the ideal solution

Sl. No.	*Relative closeness*	*Ranking*	*SN ratio*
1	0.365711	8	-8.7372
2	0.762615	2	-2.3539
3	0.433448	6	-7.2613
4	0.398983	7	-7.9809
5	0.607732	4	-4.3258
6	0.560562	5	-5.0275
7	0.676951	3	-3.3889
8	0.82038	1	-1.7197
9	0.310392	9	-10.1618

Table 3.11 Mean response Table for Signal to Noise Ratios of MPCIs

Level	N	f	d
1	-6.11746	-6.70234	-5.16149
2	-5.77807	-2.79978	-6.83220
3	-5.09011	-7.48353	-4.99196
Delta (max.-min.)	**1.02735**	**4.68374**	**1.84024**
Rank	**3**	**1**	**2**

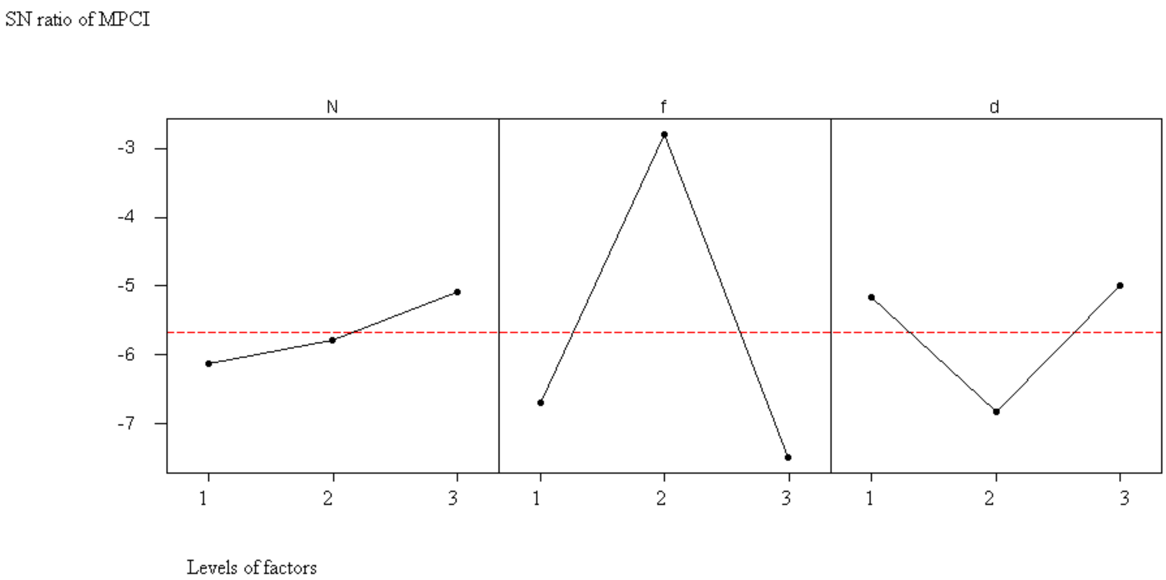


Figure 3.1: Evaluation of optimal setting (SN ratio plot of MPCIs)

Specifications of Lathe Used

Capacity	mm	Inches
Centre height	200	7-7/8
Centre Distance	750-1000	30-40
Swing Over Bed	400	15-3/4
Swing Over gap	560	22
Swing Over Carriage	375	14-3/4
Swing Over Cross Slide	245	9-5/8
Bed width	250	10
Gap length in front of face plate	120	4-3/4
HEAD STOCK		
Main Spindle Bore	42	1-5/8
Main Spindle Nose	DIN 55027-5	Cam-lock No.-5
Main Spindle Morse Taper	4	4
9 Speed Range	60-2000	60-2000
THREAD AND FEED BOX		
44 Longitudinal Feeds	0.05-0.75	0.0018-0.026
44 Cross Feeds	0.025-0.375	0.0005-0.0076
44 Metric Thread	0.5-7.5	0.5-7.5
44 Whitworth Threads in T.P. 1	60-4	60-4
44 Modular Thread	0.25-3.75	0.25-3.75
44 Pitch Diametral Threads	120-8	120-8
Thread of Lead Screw	6	4h/1
SLIDE AND CARRIAGE		
Cross slide Travel	245	9-5/8
Tool Post Slide travel	120	4-3/4
Maximum Tool Dimension	20*20	¾-3/4
TAILSTOCK		
Tailstock Barrel Diameter	58	2-9/32
Tailstock barrel Travel	200	7-7/8
Tailstock Taper	4	4
MOTORS		
Main Motor Power in KW	4	4
Pump Motor Power in KW	.06	0.06
STEADIES		
Max~Min Capacity of flexed Steady	10-130	3/8-5
Max~Min Capacity of travelling Steady	10-80	3/8-3-3/16

Chapter 4
Application of Desirability Function, Utility Theory and Fuzzy based Taguchi Method

4.1 Coverage

Glass fiber reinforced polymer (GFRP) is widely used in various engineering application due to its excellent properties over other engineering materials. The various advantages comprise high strength to weight ratio, toughness, excellent corrosion and thermal resistance **(Adeel et al., 2010)**. **Hussain et al. (2010)** suggested that productivity and quality are the two important aspects of machining process. Surface roughness and material removal rate greatly influence the performance of mechanical parts and the production cost. So, quality and productivity is to be monitored simultaneously at every stage and actions are to be taken in case of deviation from the target.

Taguchi method is a statistical method developed by *Dr. Genichi Taguchi* to improve the quality of manufactured goods. Professional statisticians have welcomed the goals and improvements brought about by Taguchi methods, particularly by Taguchi's development of designs for studying variation in the output from targeted value. However, the method is criticized due to inability to solve multi-objective optimization proposals.

In order to overcome this, utility theory, grey relation theory desirability function approaches have been reported and well documented in literature. These are widely being applied in combination with Taguchi method. The disadvantages of aforesaid techniques arise from (i) improper response weight assignment and (ii) unaccounted response correlation as described in **Chapter 1**. Assignment of response priority weight depends on the discretion of decision maker which may result variation in the optimal results. Moreover, it is assumed that responses are uncorrelated. Interdependence of the responses has been assumed negligible which creates imprecision, uncertainty as well as vagueness in the final solution. To avoid those limitations, **desirability function (DF)** as well as **utility theory (UT)** based on **fuzzy inference system (FIS)** has been proposed in the present chapter. Desirability based fuzzy approach has been reported by **Singh et al. (2011)** to optimize bead geometry parameters in submerged arc welding (SAW) which has been used for meaningful logical aggregation of multiple responses into a single Multi-Performance-Characteristic Index (MPCI). MPCI has been optimized finally by Taguchi method.

4.2 Experimentation

The experimental layout (domain of process parameters and orthogonal array design of experiment) has been selected similar to that described in **Chapter 3 (Tables 3.2-3.3)**. The experimental set up, cutting tool and measuring instruments that have been used here are similar as described in **Chapter 3**. GFRP polyester composite has been selected as specimen whose compositions have already been furnished in **Chapter 3 (Table 3.1)**. The response features selected in this experimentation were material removal rate (MRR) and roughness average (R_a) of the machined composite product. Experimental data have been shown in **Table 4.1**.

4.3 Application of DF-Fuzzy based Taguchi Method

Block diagram of the proposed methodology has been furnished in **Appendix 4**. Experimental data related to turning of GFRP polyester composite corresponding to L_9 orthogonal array (OA) design of experiment **(Table 3.3** of **Chapter 3)** have been explored to calculate desirability values of individual quality attributes: MRR and $R_{a(avg)}$. For the surface roughness parameter; a

Lower-the-Better (LB) criterion has been used. For MRR; a Higher-the-Better (HB) criterion has been selected. The objective is to improve surface finish; which means roughness value should be as less as possible. Similarly, in order to improve productivity, MRR should be as high as possible. Individual desirability measures of multi-responses have been furnished in **Table 4.2**. The individual desirability values of the responses have been treated as inputs in fuzzy inference system (FIS). The equivalent single output has been defined as (Multi-Performance Characteristic Index) MPCI. MPCI has been finally optimized (maximized) using Taguchi method. Taguchi's HB (Higher-the-Better) criterion has been explored to maximize the MPCI.

$$S/N = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right] \tag{4.1}$$

Here, n is the number of measurements, and y_i the measured i_{th} characteristic value i.e. i_{th} quality indicator.

The fuzzy inference system (FIS) used in the present study **(Fig. 4.1)** consists of two inputs and a single output. Three membership functions **(Figs. 4.2-4.3)** have been assigned to each of the input variables (desirability value of MRR and desirability value of $R_{a(avg)}$ respectively). These membership functions are: "Low", "Medium", and "High". Five membership functions have been used for MPCI **(Fig. 4.4)**. These are "Very Low", "Low", "Medium", "High" and "Very High". **Fig. 4.5** shows fuzzy based rule matrix. Fuzzy logic converts linguistic inputs into linguistic output. Linguistic output is again converted to numeric values (MPCI) by defuzzification method. **Fig. 4.6** represents optimal parametric combination (N_1 f_2 d_2). Optimal result has been validated by satisfactory confirmatory test. From mean response table **(Table 4.3)** it has been found that feed rate is the most influential parameter followed by cutting speed and depth of cut in controlling MPCI values.

4.4 Application of UT-Fuzzy based Taguchi Method

Block diagram of the proposed methodology has been furnished in **Appendix 5**. Experimental data related to turning of GFRP polyester composite corresponding to L_9 orthogonal array (OA) design of experiment **(Table 4.4)** have been investigated to calculate utility values of individual quality attributes: MRR and $R_{a(avg)}$. For the surface roughness parameter, a Lower-the-Better (LB) criterion has been used. For MRR, a Higher-the-Better (HB) criterion has been used. The justification of individual response selection criteria have already been discussed in **Section 4.3** of this chapter. It is felt that a compatible balance should be there for quality (surface quality in the present case) as well as productivity. Individual utility measures of multi-responses have been furnished in **Table 4.5**. The common task is to convert initially these multi-objectives into an equivalent single objective function. The individual utility values of the responses have been treated as inputs in fuzzy inference system (FIS). The equivalent single output has been defined as MPCI. MPCI has been finally optimized (maximized) using Taguchi method. Taguchi's HB (Higher-the-Better) criterion has been explored to maximize the MPCI.

FIS (shown in **Fig. 4.7**) used in the present study consists of two inputs and a single output. Three membership functions **(Figure 4.8-4.9)** have been assigned to each of the input variables (utility value of MRR and utility value of R_{avg} respectively). These membership functions are: "Low", "Medium", and "High". For the output (MPCI), five membership functions have been used: "Very Low", "Low", "Medium", "High" and "Very High" **(Fig. 4.10)**.

Fig. 4.11 shows fuzzy based rule matrix. Fuzzy logic converts linguistic inputs into linguistic output. Linguistic output is again converted to numeric values (MPCI) by defuzzification method. **Fig. 4.12** represents optimal parametric combination (N_2 f_3 d_2). Optimal result has been validated by satisfactory confirmatory test. It has been found that predicted signal to noise ratio at optimal setting is 18.5255 (maximum from all entries in **Table 4.5**).Because S/N ratio is always to be maximized which means minimum quality loss (in the present case). From mean response table **(Table 4.6)** it has been found that feed rate is the most influential parameter followed by cutting speed and depth of cut in controlling MPCI values.

4.5 Concluding Remarks

In this study desirability function and utility theory based fuzzy models have been developed consisting of two input variables (material removal rate and roughness average) and one output variable i.e. MPCI. Through this way a multi-response optimization problem has been converted to an equivalent single objective optimization problem which has been further solved by Taguchi philosophy. Accuracy in prediction of the model analysis can be subsequently increased by increasing number of membership function in the fuzzy system. The proposed procedure has been simple, effective in developing a robust, versatile and flexible experiment process. In adapting FIS models it is not necessary to assign response priority weights.

In the contrary, in traditional desirability function based Taguchi approach, it has been viewed that desirability values of individual responses (d_i) are generally aggregated **(Eq. 4.2)** to compute an overall desirability (D). Optimal process environment is then selected through maximizing overall desirability using Taguchi method.

$$D = \left(d_1^{w_1} . d_2^{w_2} ... d_n^{w_n}\right)^{\frac{1}{\Sigma w}} \quad \textbf{(4.2)}$$

Here w_i is the priority weight of i_{th} response.

Similarly, in traditional utility concept based Taguchi approach, utility values (preference numbers) of individual responses (U_i) are accumulated **(Eq. 4.3)** to compute an overall utility degree (U). Optimal parameter setting is then selected through maximizing overall utility degree using Taguchi method.

$$U = \frac{\sum_{i=1}^{n} U_i w_i}{\sum_{i=1}^{n} w_i} \quad \textbf{(4.3)}$$

Here w_i is the priority weight of i_{th} response.

Therefore, traditional desirability function/utility concept based Taguchi method requires response priority weights; which are uncertain and mainly dependent on individuals' (Decision-makers') perception.

The proposed FIS model has been found effective in aggregating multi-inputs towards estimating a unique output. Therefore, instead of computing overall desirability (D) or overall utility degree (U); individual desirability values $(d_i)_{i=1,2,\ldots,n}$ and individual utility values $(U_i)_{i=1,2,\ldots,n}$ have been fed as inputs to the fuzzy inference system. Based on fuzzy rule base reasoning, FIS combines these multi-inputs into an equivalent single performance index. Assignment of response weights is not required for this methodology.

However, the concept developed hare is based on an assumption. It has been assumed that responses are uncorrelated. But in practice there may present some extent of correlation among various process responses. To this end next chapter attempts to develop an integrated optimization philosophy that can efficiently take care the aspects of response correlation as well as uncertainties arising towards improper response weight assignment. Principal Component Analysis (PCA) has been embedded in fuzzy-based Taguchi method.

Table 4.1 Experimental data

Sl. No	*MRR (mm^3/min)*	*Trial 1*	*Trial 2*	*$R_{a(avg)}$ (μm)*
		R_{a1}(μm)	*R_{a2}(μm)*	
1	2747.52	3.74	4.1	3.92
2	5615.76	4.1	3.62	3.86
3	12352.9	4.72	4.1	4.41
4	4421.05	3.36	4.26	3.81
5	10869.6	4.1	4.68	4.39
6	15245.9	5.14	6.06	5.6
7	6896.55	5.88	5.68	5.78
8	11797.8	4.32	5.18	4.75
9	26511.6	4.86	5	4.93

Table 4.2 Individual desirability values and computed MPCI

Sl. No.	*Desirability of ($R_{a(avg)}$)*	*Desirability of (MRR)*	*MPCI*	*S/N Ratio (dB)*
1	0.944162	0.000000	0.463	-6.6884
2	0.974619	0.120696	0.551	-5.1770
3	0.695431	0.404197	0.54	-5.3521
4	1.000000	0.070423	0.544	-5.2880
5	0.705584	0.34178	0.515	-5.7639
6	0.091371	0.525936	0.33	-9.6297
7	0.000000	0.174592	0.194	-14.2440
8	0.522843	0.380839	0.446	-7.0133
9	0.431472	1.000000	0.701	-3.0856

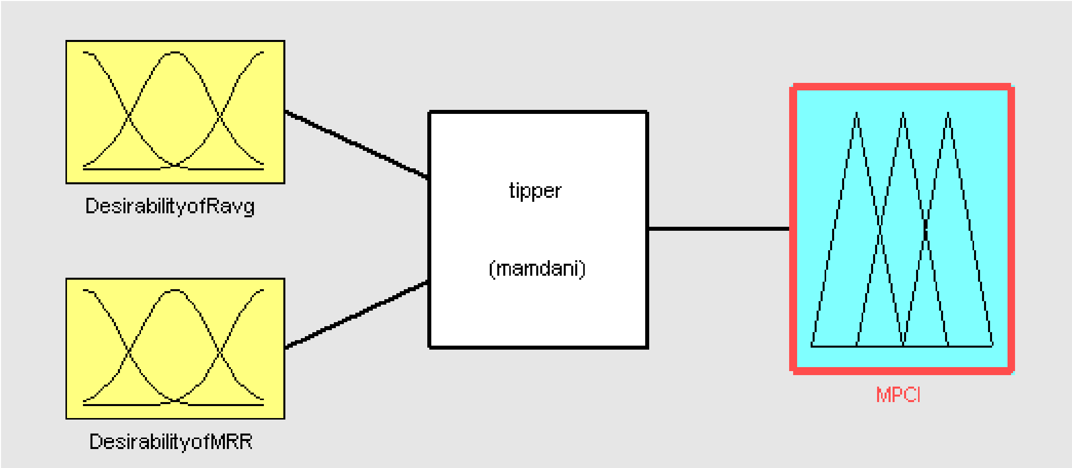


Figure 4.1: Proposed FIS model

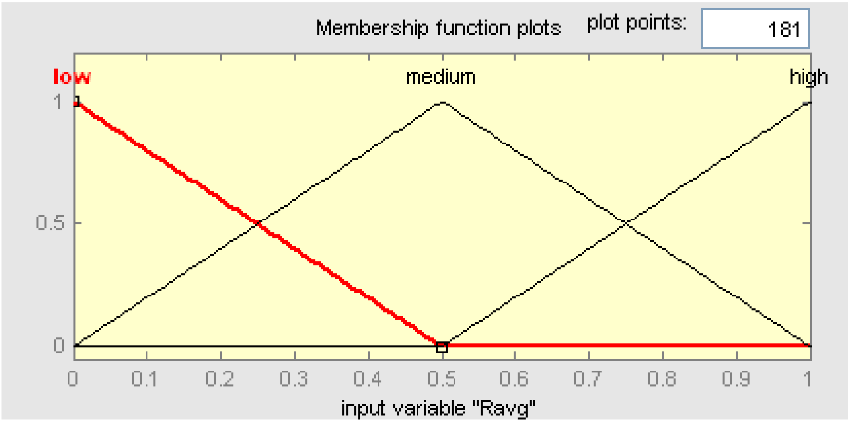


Figure 4.2: Membership Functions (MFs) for desirability of $R_{a(avg)}$

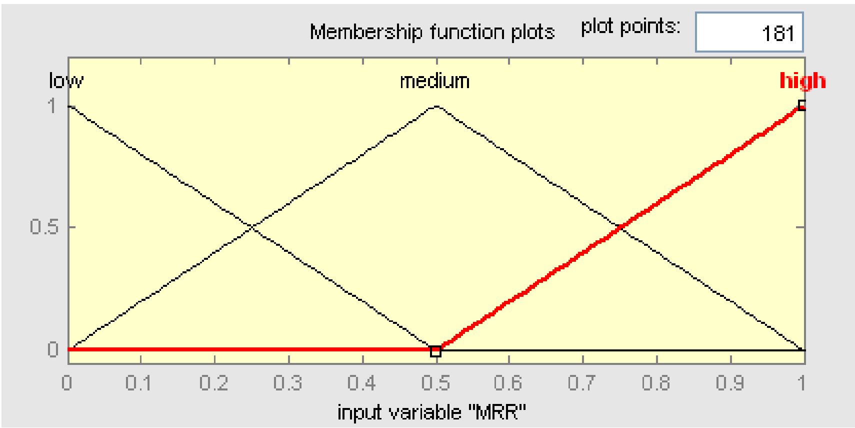


Figure 4.3: Membership Functions (MFs) for desirability of MRR

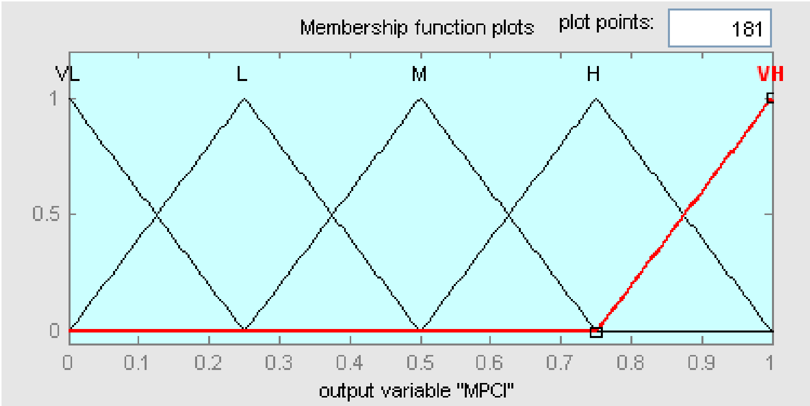


Figure 4.4: Membership Functions (MFs) for desirability of MPCI

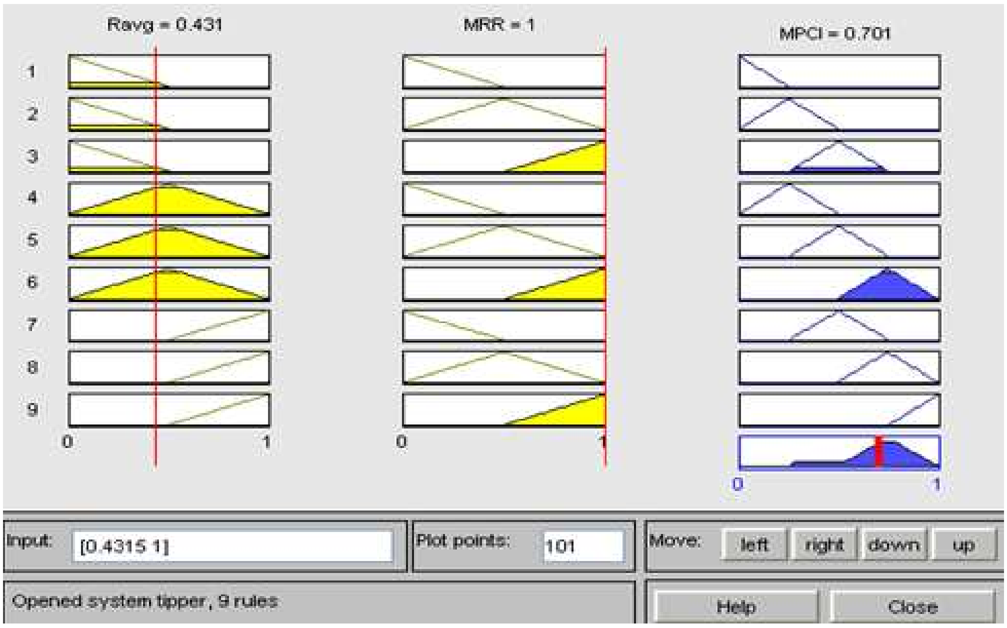


Figure 4.5: Fuzzy rule base reasoning

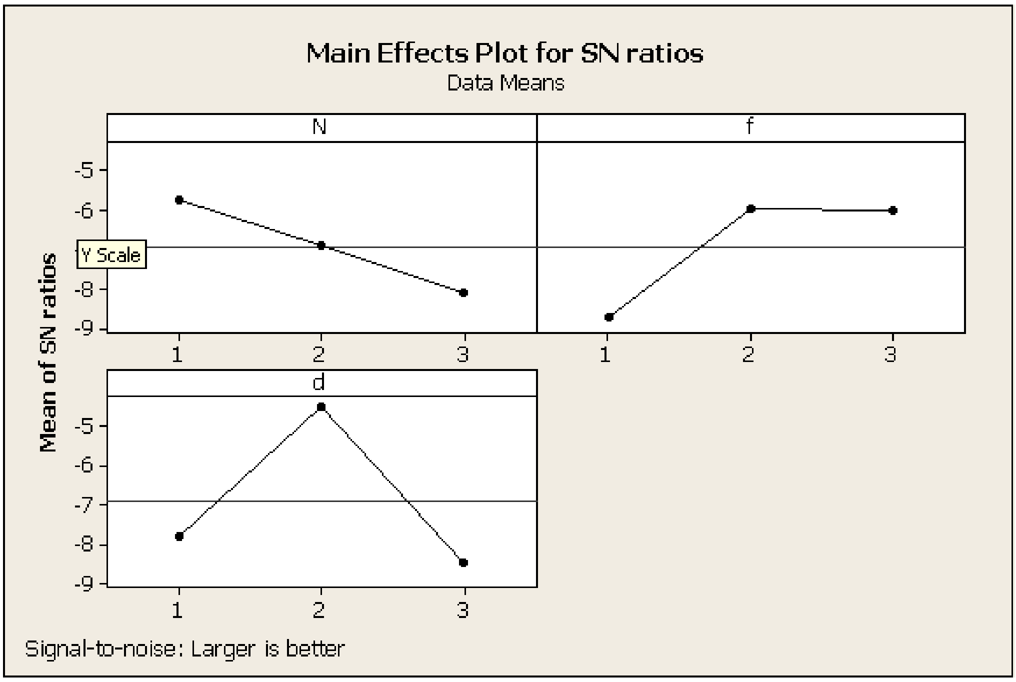


Figure 4.6: Evaluation of optimal setting (S/N ratio plot of MPCIs)

Table 4.3 Mean response table (S/N Ratios of MPCIs)

Level	N	f	d
1	-5.739	-8.740	-7.777
2	-6.894	-5.985	-4.517
3	-8.114	-6.022	-8.453
Delta = (Max.-Min.)	2.375	2.755	3.936
Rank	3	2	1

Table 4.4 Experimental data

Sl. No.	*MRR (mm^3/min)*	*Trial 1*	*Trial 2*	*$R_{a(avg)}$ (μm)*
		R_{a1} (μm)	*R_{a2} (μm)*	
1	2747.52	3.18	3.57	3.375
2	5615.76	4.47	4.7	4.585
3	12352.9	3.25	3.13	3.19
4	4421.05	3.04	2.33	2.685
5	10869.6	3.52	3.6	3.56
6	15245.9	4.49	3.08	3.785
7	6896.55	5.03	4.07	4.55
8	11797.8	2.86	6.22	4.54
9	26511.6	2.28	2.75	2.515

Table 4.5 Individual utility values and computed MPCI

Sl. No.	*Utility of ($R_{a(avg)}$)*	*Utility of (MRR)*	*MPCI*	*S/N Ratio (dB)*
1	4.59196	0	2.32	7.3098
2	0	2.838212164	2.09	6.4029
3	5.436847	5.967993913	5.38	14.6156
4	8.019721	1.888539124	4.87	13.7506
5	3.792171	5.460095051	4.62	13.2928
6	2.873684	6.257005879	4.55	13.1602
7	0.114844	3.653867636	2.29	7.1967
8	0.147819	5.785423394	3.1	9.8272
9	8.999994	8.999999777	8.28	18.3606

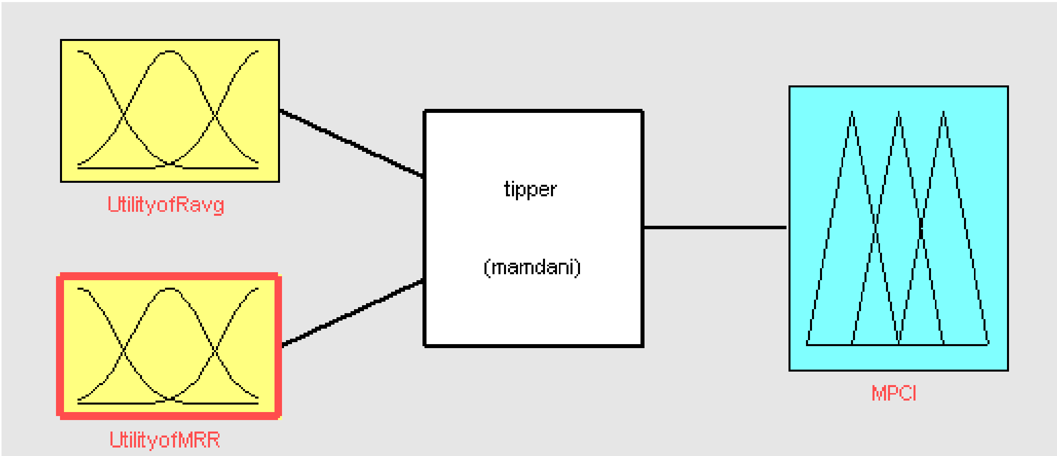


Figure 4.7: Proposed FIS model

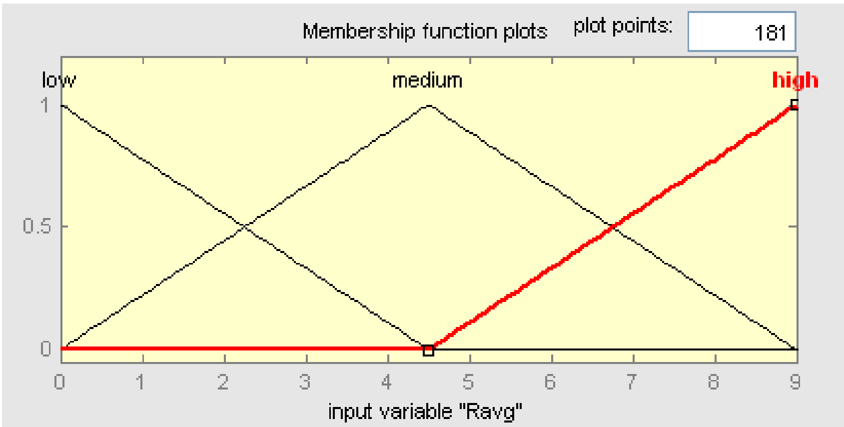


Figure 4.8: Membership Functions (MFs) for utility of $R_{a(avg)}$

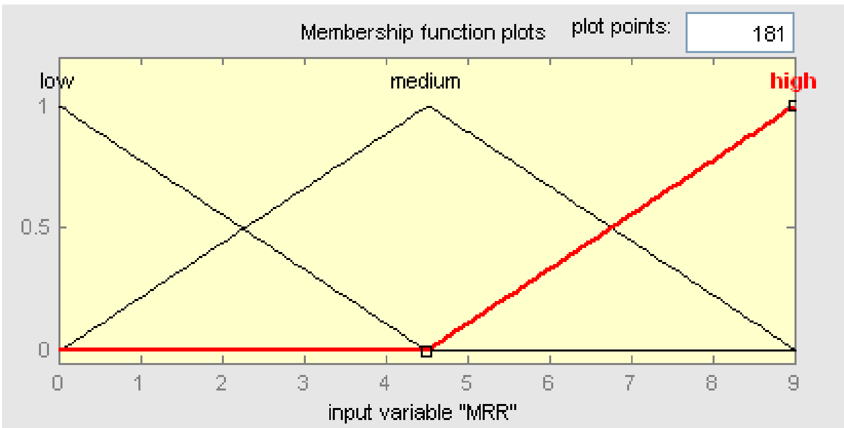


Figure 4.9: Membership Functions (MFs) for utility of MRR

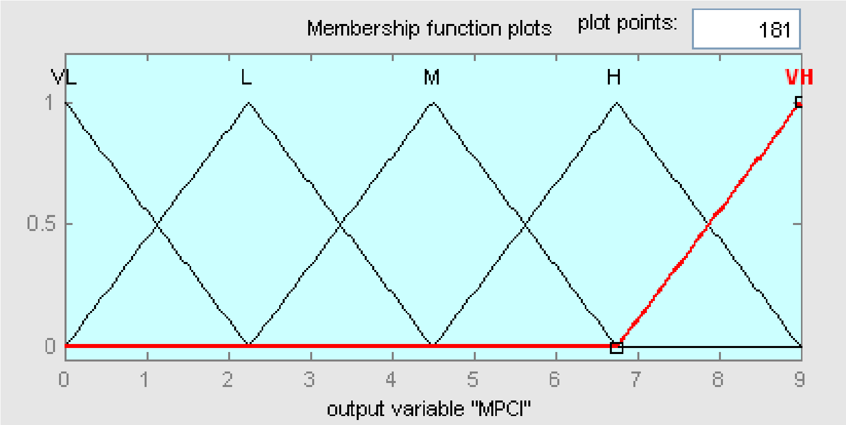


Figure 4.10: Membership Functions (MFs) for MPCI

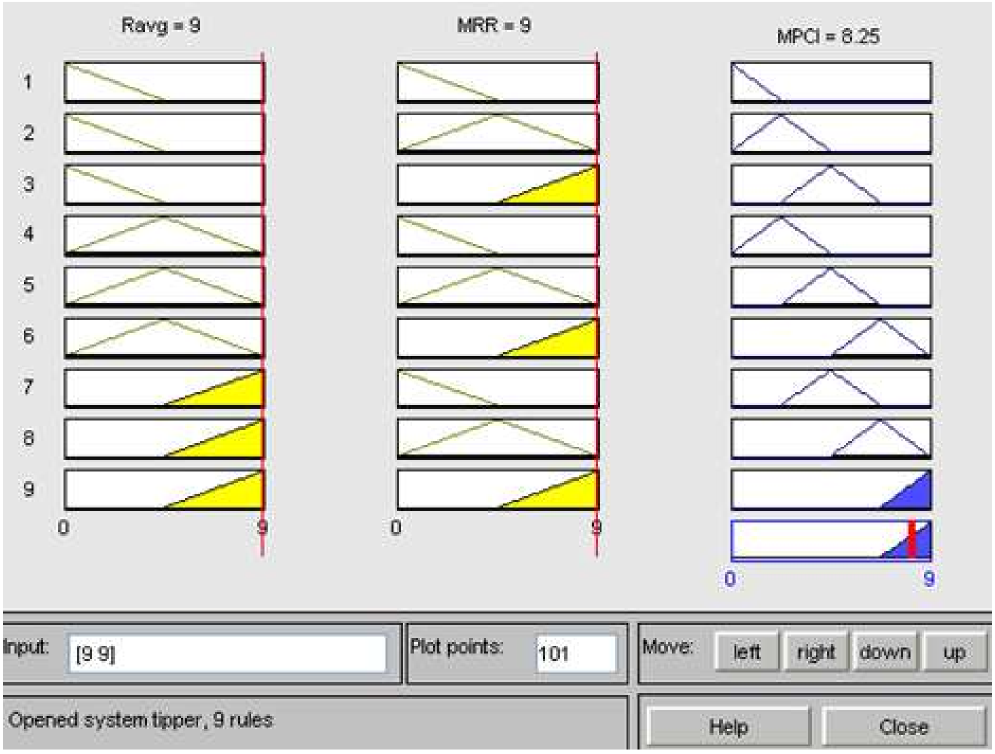


Figure 4.11: Fuzzy rule base reasoning

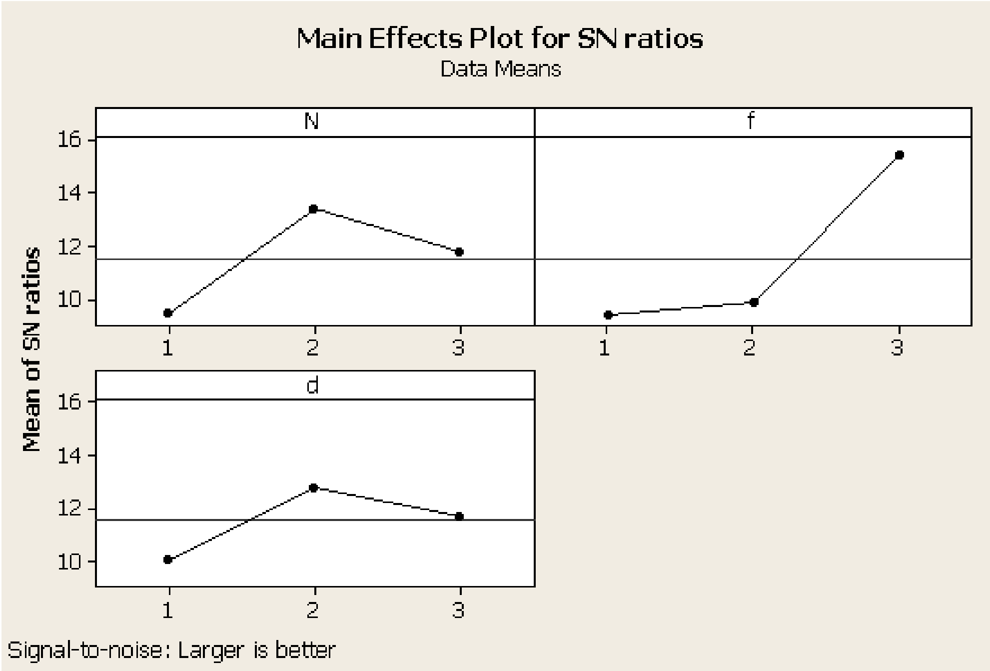


Fig. 4.12: Evaluation of optimal setting (S/N ratio plot of MPCIs)

Table 4.6 Mean response table (S/N Ratios of MPCIs)

level	N	f	d
1	9.443	9.419	10.099
2	13.401	9.841	12.838
3	11.795	15.379	11.702
Delta = (Max.-Min.)	3.958	5.960	2.739
Rank	2	1	3

Chapter 5
Application of PCA-Fuzzy based Taguchi Method

5.1 Coverage

A PCA-fuzzy expert system integrated with Taguchi method has been proposed here. PCA has been used to eliminate response correlation and to convert correlated responses into uncorrelated quality indices. Uncorrelated quality indices are to be fed in Fuzzy Inference System (FIS) to compute MPCI. Fuzzy logic is an efficient tool immensely applied in the field of decision engineering **(Azadeh et al., 2010; Kumar et al., 2011)**. The single output of FIS (i.e. MPCI) has been optimized by Taguchi method.

5.2 Experimentation

The present study has aimed to optimize multiple surface roughness characteristics and MRR of turned glass fiber reinforced polyester composites. An appropriate process environment (parameter setting) has been evaluated to minimize various measures (indices) of product surface roughness characteristics as well as to maximize MRR. Optimal process condition has been determined from the analysis of experimental data.

The present study has been done through the following plan of experiments.

A. Checking and preparing the centre lathe ready for performing the machining operation.

B. Cutting GFRP bars and performing initial turning operation in lathe to get desired dimension ($\phi 50 \times 150$) of the work pieces.

C. Calculating weight of each specimen by the high precision digital balance meter before machining.

D. Performing straight turning operation on specimens in various cutting environments involving various combinations of process control parameters like spindle speed, feed and depth of cut.
E. Calculating weight of each machined GFRP bars again by the digital balance meter.
F. Calculating MRR of each experiment.
G. Measuring surface roughness with the help of a portable stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+, UK).

Glass fiber reinforced polyester composite has been selected as work piece material. The specifications of the work piece material are same as shown in **Chapter 3 Table 3.1**. The ISO specification of the tool holder used for the turning operation is a WIDAX tool holder PC LNR 2020 K12 and the tool insert used for the study are carbide K-20, (CNMA 120408). In the present study, spindle speed (N, rpm), feed rate (f, mm/min) and depth of cut (d, mm), have been selected as design factors while other parameters have been assumed to be constant over the experimental domain. The process variables (design factors) with their values at different levels have been same as considered in **Chapter 3 Table 3.2**. It is known that the selection of the values of the variables is limited by the capacity of the machine used in the experimentation as well as the recommended specifications for different work piece and tool material combinations. Therefore, three levels have been selected for each of the aforesaid three factors. In the present investigation, Taguchi's L_9 orthogonal array (OA) design (without factorial interaction) has been considered for experimentation (shown in **Chapter 3 Table 3.3**). The machine used for turning is PINACHO lathe (specifications given at the end of **Chapter 3**). The surface roughness parameters have been measured using the stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+). The values of measured roughness parameters: (average of two trials) R_q, R_a, R_t, R_{ku}, R_z, R_{sm} along with material removal rate (MRR) have been shown in **Table 5.1**.

5.3 Application of PCA-Fuzzy Based Taguchi Approach

Procedural hierarchy of the proposed PCA-fuzzy based Taguchi approach has been furnished in **Appendix 6**. Experimental data (corresponding to **Table 5.1**) have been converted into corresponding S/N ratios using **Eqs. 5.1-5.2**. In order to analyze all surface roughness parameters, a Lower-the-Better (LB) criterion and for MRR, a Higher-the-Better (HB) criterion has been selected.

$$S/N = -10\log\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right](Lower-the-Better) \tag{5.1}$$

$$S/N = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right](Higher-the-Better) \tag{5.2}$$

Here, n is the number of measurements, and y_i the measured i_{th} characteristic value i.e. i_{th} quality indicator.

Computed S/N ratios have been furnished in **Table 5.2**. These S/N ratios have then been normalized based on Higher-the-Better (HB) criteria using the following equation.

For Higher -the-Better (HB) criterion, the normalized data can be expressed as:

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)} \tag{5.3}$$

Here,

$x_i(k)$ is the value of the response k for the i^{th} experiment, $\min y_i(k)$ is the smallest value of $y_i(k)$ for the k^{th} response, and $\max y_i(k)$ is the largest value of $y_i(k)$ for the k^{th} response.

Normalized S/N ratios have been furnished in **Table 5.3**. Pearson's correlation coefficient has been evaluated next and tabulated in **Table 5.4**. In all cases nonzero values of correlation coefficients depict that responses (S/N ratios of all output features) are mutually correlated. In order to avoid response correlation, PCA has been applied to convert correlated responses into uncorrelated quality indices called principal components (PCs). **Table 5.5** represents principal component analysis i.e. Eigen analysis of the correlation Matrix. After finding Eigen values, Eigen vectors and correlation coefficients; factor analysis has been carried out to summarize the data structure in a few dimensions of the data and also to explain the dimensions associated with large data variability. An orthogonal rotation simply rotates the axes to give a different perspective. The different methods available are EQUIMAX, VARIMAX, QUARTIMAX, and ORTHOMAX. A parameter, gamma is determined during the rotation method. If the method with a low value of gamma is used, the rotation will tend to simplify the rows of the loadings and if the method with a high value of gamma is used the rotation will tend to simplify the columns of the loadings. VARIMAX rotation has been used in the present case because it maximizes the variance of the squared loadings. Rotated factor loadings and communalities in VARIMAX rotation has been shown in **Table 5.6**. **Fig. 5.1** reveals scree plot obtained in PCA analysis on normalized responses. It has been observed that first four principal components (PCs) can satisfactorily explain 99.8% data variation. Therefore, only these PCs have been considered for further analysis. Remaining PCs have been ignored.

Individual principal components (PC1 to PC4) thus computed have been given in **Table 5.7**. PCs have been normalized by using Higher-the-Better (HB) criteria **(Eq. 5.2)** and corresponding normalized values have been shown in **Table 5.8**. Normalized PCs have been fed as inputs in Fuzzy Inference System (FIS) **(Fig. 5.2)**. The output of the fuzzy inference system has been defined as MPCI **(Table 5.8)**. This Multi-Performance Characteristic Index (MPCI) has been finally optimized by using Taguchi methodology. Higher- the- Better (HB) criterion has been used for optimizing (maximizing) the MPCI **(Eq. 5.2)**.

In calculating MPCI in FIS system, various membership functions (MFs) **(Figs. 5.3-5.6)** have been assigned to the seven input variables: The selected membership functions for input variables are given below.

PC1: “Low” and “Medium”.

PC2: “Low”, “Medium” and “High”

PC3: “Very Low”, “Low”, “Medium”, “High” and “Very High”.

PC4: “Low”, “Medium, “High”.

Five membership functions have been selected for MPCI: “Very Low”, “Low”, “Medium”, “High”, and “Very High” **(Fig. 5.7)**. 15 fuzzy rules **(Table 5.9)** have been explored for fuzzy reasoning **(Figure 5.8)**. Fuzzy based rule matrix has been constructed and shown in **Table 5.9 (Sivarao et al., 2009; Ali and Zhang, 1999; Gupta et al., 2011)**. Fuzzy logic converts linguistic inputs into linguistic output. Linguistic output is again converted to numeric values (MPCI) by defuzzification method. Numeric values of MPCIs have been tabulated in **Table 5.8** with corresponding S/N ratio. S/N ratios of MPCIs have been calculated using Higher-the-Better (HB) criterion. **Fig. 5.9** represents optimal parametric combination (N_3 f_3 d_1). Optimal result has been validated by satisfactory confirmatory test. Predicted value of S/N ratio of MPCI becomes -1.26465 and predicted mean is 0.831 (highest among all entries in **Table 5.8**). In confirmatory experiment the value came -1.1367. So, quality has improved using the said optimal setting. **Table 5.10** represents mean values table of MPCIs. The degree of influence of various factors on MPCI can be estimated from this table. It shows that feed rate is the most significant factor on influencing MPCIs following with spindle speed and depth of cut.

The aforesaid approach seemed to be effective as it simultaneously optimizes product quality (multiple surface roughness estimates, in the present case) as well as productivity (MRR). The outcome of this study bears significant managerial implications. The predicted optimal setting can satisfactorily be used in mass production line as it maintains twofold requirements of quality and productivity. It reduces cost for trial and error experimentation, does not solely rely on operators past experience, personal skill; and saves considerable time and production cost.

5.4 Concluding Remarks

In this study, PCA and fuzzy rule based model has been developed using four input variables with single output i.e. MPCI. By this way a multi-response optimization problem has been converted into an equivalent single objective optimization problem which has been further solved by Taguchi philosophy. The proposed procedure is simple, effective in developing a robust, versatile and flexible mass production process. Response correlation is eliminated by PCA analysis. PCs can be aggregated further to compute an overall performance index (MPCI). In the proposed model it is not required to assign individual response weights. FIS can efficiently take care of this aspect into its internal hierarchy. Degree of influence of various process control factors can be investigated easily. Accuracy in prediction of the model analysis can be subsequently increased by assigning adequate fuzzy rules as well as by increasing number of membership functions in the fuzzy inference system. This approach can be recommended for continuous quality improvement and off-line quality control of a process/product in any manufacturing/ production environment.

The study bears a significant impact on industrial application of the process for manufacture of composite products in an economic manner. Process optimization can evaluate an appropriate process environment capable of producing desired quality product. It reduces time and cost for trial and error experimentation and the obtained best process environment can be used for mass production line. Work can be extended to study the mechanics of chip formation, behavior of cutting forces and related aspects at that particular process environment. The developed optimization methodology may be used to other production processes as well.

Table 5.1 Response data (various surface roughness parameters and MRR)

Sl. No.	R_q (µm)	R_a (µm)	R_t (µm)	MRR(mm^3/min)	R_{ku}	R_z (µm)	R_{sm} (mm)
1	4.14	3.375	24.25	2747.52	2.99	18.6	0.10065
2	5.735	4.585	36.5	5615.76	3.995	25.75	0.133
3	4.015	3.19	25.6	12352.9	4.35	18.45	0.10205
4	3.43	2.685	21.45	4421.05	4.93	16.05	0.194
5	4.58	3.56	28.1	10869.6	5.33	20.55	0.09605
6	4.65	3.785	28.95	15245.9	3.565	20.75	0.1255
7	5.595	4.55	35.4	6896.55	3.49	25.45	0.1145
8	5.615	4.54	39.45	11797.8	5.215	24.85	0.1145
9	3.18	2.515	19.4	26511.6	4.835	14.05	0.114

Table 5.2 S/N ratio data of all experimental arrangements

Sl. No.	S/N Ratio of experimental data						
	R_q (dB)	R_a (dB)	R_t (dB)	MRR(dB)	R_{ku} (dB)	R_z (dB)	R_{sm} (dB)
1	-12.3400	-27.6942	-9.5134	-25.3903	19.9437	-10.5655	68.7788
2	-15.1707	-31.2459	-12.0303	-28.2155	17.5230	-13.2268	74.9882
3	-12.0737	-28.1648	-12.7698	-25.3199	19.8237	-10.0758	81.8354
4	-10.7059	-26.6285	-13.8569	-24.1095	14.2440	-8.5789	72.9105
5	-13.2173	-28.9741	-14.5345	-26.2562	20.3501	-11.0290	80.7243
6	-13.3491	-29.2330	-11.0412	-26.3404	18.0271	-11.5613	83.6631
7	-14.9560	-30.9801	-10.8565	-28.1138	18.8239	-13.1602	76.7726
8	-14.9870	-31.9209	-14.3451	-27.9065	18.8239	-13.1411	81.4360
9	-10.0485	-25.7560	-13.6879	-22.9535	18.8619	-8.0108	88.4687

Table 5.3 Normalization of the performance evaluation criteria

Sl. No.	Normalized (Nor) S/N ratio of the responses						
	R_q	R_a	R_t	MRR	R_{ku}	R_z	R_{sm}
1	0.447366366	0.31439277	0	0.463093881	0.066556394	0.48978144	0
2	1	0.89050917	0.501264663	1	0.46299602	1	0.315359651
3	0.395376986	0.39072815	0.648543148	0.449714937	0.086208873	0.39589724	0.663111544
4	0.12834329	0.14152703	0.865049491	0.219688331	1	0.10891488	0.209838547
5	0.618640428	0.5220036	1	0.627651083	0	0.57864264	0.606681598
6	0.644371559	0.56399942	0.304275955	0.643652604	0.380439233	0.68069402	0.755935784
7	0.958084417	0.84739412	0.267491187	0.980672748	0.249946775	0.9872316	0.405984794
8	0.964136504	1	0.962279182	0.941277081	0.249946775	0.98356979	0.642827033
9	0	0	0.831391528	0	0.24372349	0	1

Table 5.4 Check for response correlation (Pearson's correlation coefficient)

Correlation between responses	R_q	R_t	R_{ku}	R_z	R_{sm}	R_a
R_t	0.985					
R_{ku}	-0.210	-0.090				
R_z	0.996	0.982	-0.214			
R_{sm}	-0.216	-0.166	0.167	-0.172		
R_a	0.998	0.981	-0.262	0.993	-0.223	
MRR	-0.179	-0.104	0.483	-0.225	-0.264	-0.187

Table 5.5 Principal Component Analysis: Eigen analysis of the Correlation Matrix

Eigen values	4.1168	1.4434	1.0658	0.3626	0.0084	0.0030	1.000
Eigen vectors	$\begin{bmatrix} 0.989 \\ 0.996 \\ -0.104 \\ 0.987 \\ -0.125 \\ 0.983 \\ -0.108 \end{bmatrix}$	$\begin{bmatrix} 0.084 \\ -0.022 \\ -0.957 \\ 0.081 \\ -0.095 \\ 0.140 \\ -0.262 \end{bmatrix}$	$\begin{bmatrix} -0.096 \\ -0.045 \\ 0.103 \\ -0.059 \\ 0.976 \\ -0.099 \\ -0.166 \end{bmatrix}$	$\begin{bmatrix} -0.070 \\ -0.009 \\ 0.252 \\ -0.113 \\ -0.148 \\ -0.064 \\ 0.944 \end{bmatrix}$	$\begin{bmatrix} -0.038 \\ 0.073 \\ 0.002 \\ -0.032 \\ 0.000 \\ -0.006 \\ 0.001 \end{bmatrix}$	$\begin{bmatrix} -0.011 \\ -0.010 \\ -0.000 \\ 0.050 \\ 0.000 \\ -0.029 \\ -0.000 \end{bmatrix}$	$\begin{bmatrix} -0.006 \\ -0.000 \\ -0.000 \\ 0.001 \\ 0.000 \\ 0.006 \\ -0.000 \end{bmatrix}$
Accountability Proportion (AP)	0.588	0.206	0.152	0.052	0.001	0.000	0.000
Cumulative Accountability Proportion (AP)	0.588	0.794	0.947	0.998	1.000	1.000	1.000

Table 5.6 Rotated Factor Loadings and Communalities VARIMAX Rotation

Variable	Factor1	Factor2	Factor3	Factor4	Communality
Nor of (R_q)	0.989	0.084	-0.096	-0.070	0.998
Nor of (R_t)	0.996	-0.022	-0.045	-0.009	0.995
Nor of (R_{ku})	-0.104	-0.957	0.103	0.252	1.000
Nor of (R_z)	0.987	0.081	-0.059	-0.113	0.996
Nor of (R_{sm})	-0.125	-0.095	0.976	-0.148	1.000
Nor of (R_a)	0.983	0.140	-0.099	-0.064	0.999
Nor of (MRR)	-0.108	-0.262	-0.166	0.944	1.000
Variance	3.9471	1.0262	1.0160	0.9993	6.9886
% Var	0.564	0.147	0.145	0.143	0.998

Nor: Normalized value

Table 5.7 Calculated principal components (PCs)

Sl. No.	PC1	PC2	PC3	PC4
1	1.68579	0.130419	-0.06795	-0.12767
2	3.701882	-0.32091	0.157092	0.10048
3	1.463388	-0.68611	-0.0804	0.669303
4	0.35416	-0.93712	0.987833	0.226027
5	2.150527	-0.94362	-0.17491	0.668747
6	2.342594	-0.33624	0.08456	0.567497
7	3.627014	-0.10662	-0.0816	0.164974
8	3.644675	-0.84014	-0.05411	0.566529
9	-0.22493	-1.0808	0.157507	1.11744

Table 5.8 Normalized individual principal components and computed MPCI

Sl. No.	Nor of PC1	Nor of PC2	Nor of PC3	Nor of PC4	MPCI	S/N Ratio	MEAN
1	0.486579335	1	0.091981801	0	0.5	-6.02060	0.500
2	1	0.627375704	0.285528025	0.183256501	0.5	-6.02060	0.500
3	0.42994209	0.325861528	0.081274243	0.640091074	0.75	-2.49877	0.750
4	0.147464335	0.118624197	1	0.284086127	0.5	-6.02060	0.500
5	0.604929994	0.113257707	0	0.639644538	0.5	-6.02060	0.500
6	0.653842079	0.614719044	0.223147248	0.558328381	0.651	-3.72838	0.651
7	0.980934506	0.804296494	0.080242189	0.235053086	0.625	-4.08240	0.625
8	0.985432084	0.198692228	0.103884823	0.557550958	0.75	-2.49877	0.750
9	0	0	0.285884943	1	0.75	-2.49877	0.750

Nor: Normalized value

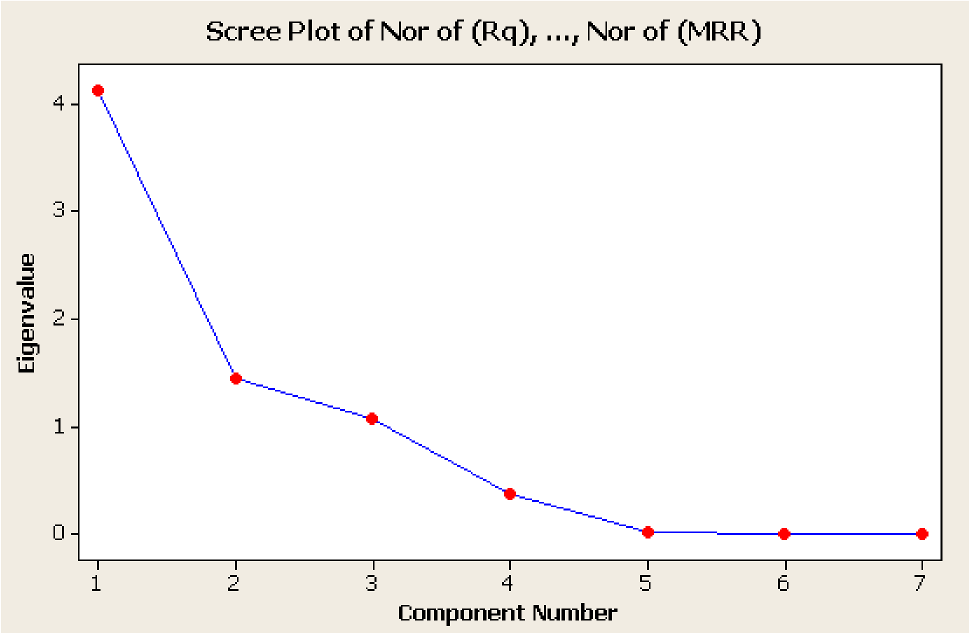


Figure 5.1: Principal component score

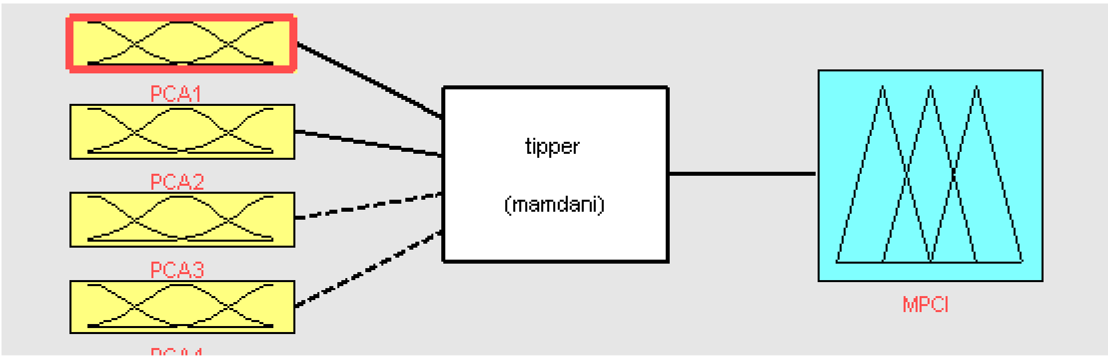


Figure 5.2: Proposed FIS model

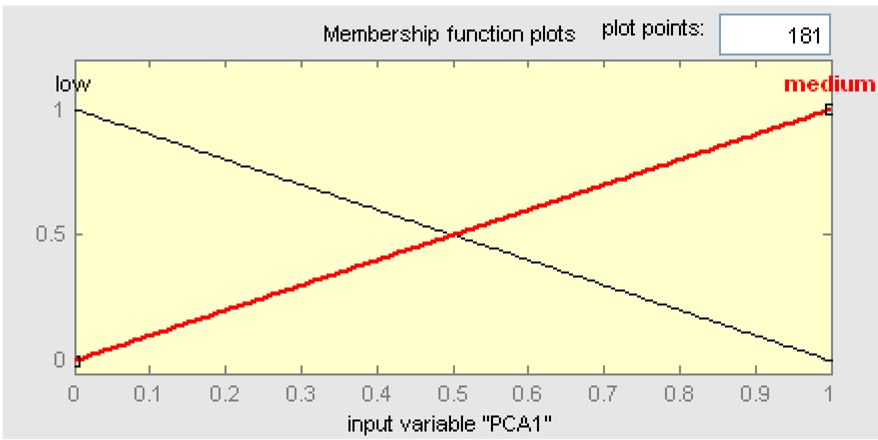


Figure 5.3: MFs for PC1

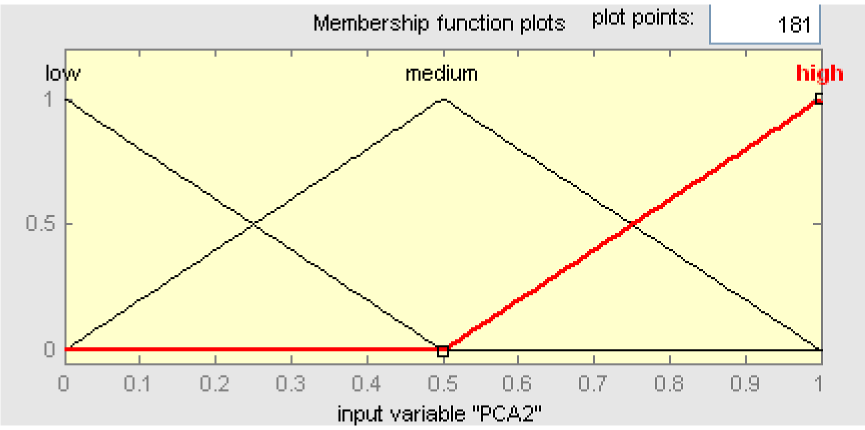


Figure 5.4: MFs for PC2

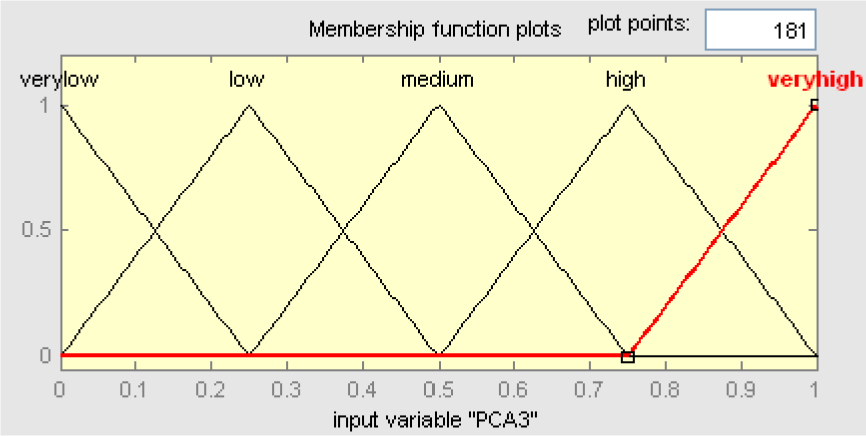


Figure 5.5: MFs for PC3

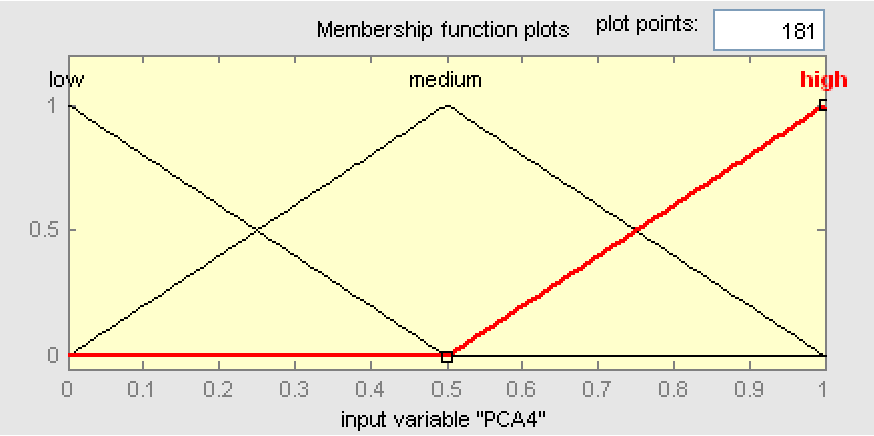


Figure 5.6: MFs for PC4

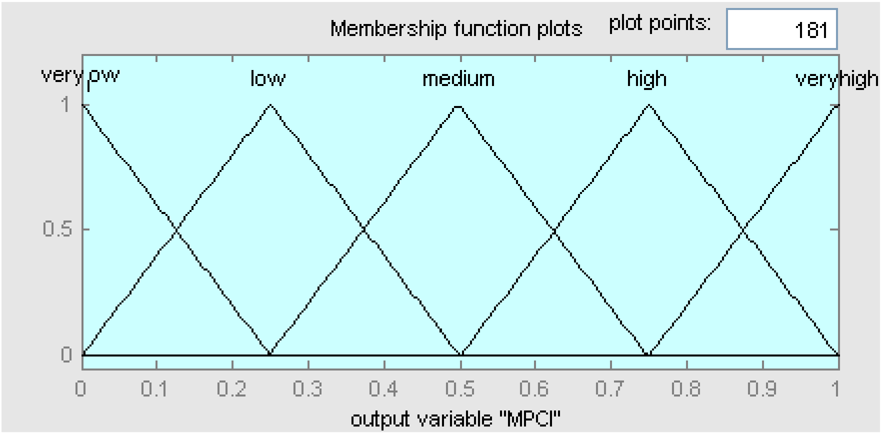


Figure 5.7: MFs for MPCI

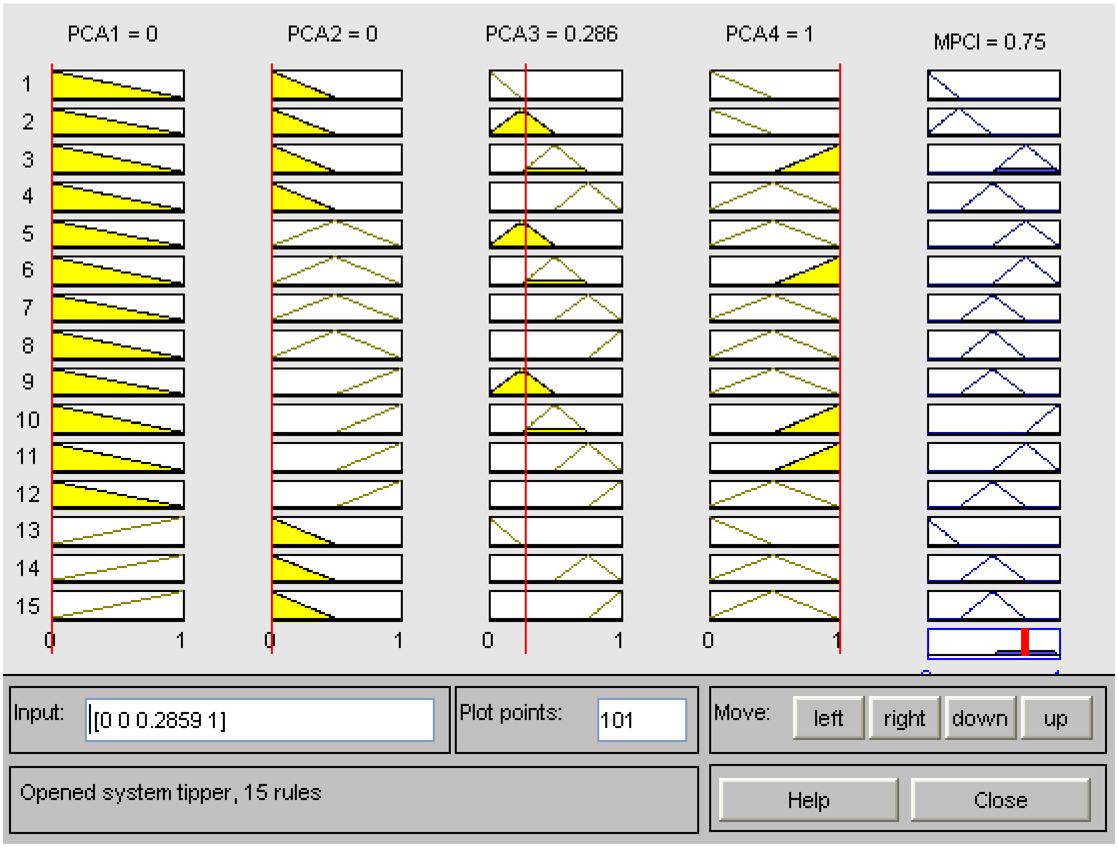


Figure 5.8: Fuzzy rule base reasoning

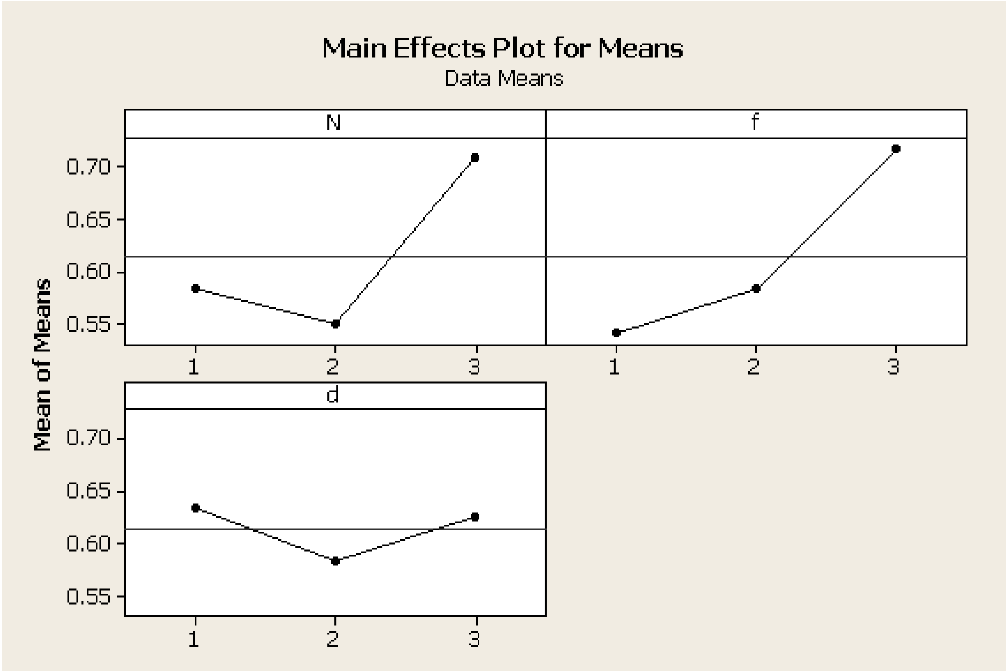


Figure 5.9: Evaluation of optimal setting (mean value plot of MPCI)

Table 5.9 Fuzzy rules

Sl. No.	If PC1	If PC2	If PC3	If PC4	Then
1	Low	Low	Very low	Low	Very low
2	Low	Low	Low	Low	Low
3	Low	Low	Medium	High	High
4	Low	Low	High	Medium	Medium
5	Low	Medium	Low	Medium	High
6	Low	Medium	Medium	High	High
7	Low	Medium	High	Medium	Medium
8	Low	Medium	Very high	Medium	Medium
9	Low	High	Low	Medium	Medium
10	Low	High	Medium	High	Very high
11	Low	High	High	High	High
12	Low	High	Very high	Medium	Medium
13	Medium	Low	Very low	Low	Very low
14	Medium	Low	High	Medium	Medium
15	Medium	Low	Very high	Medium	Medium

Table 5.10 Response table for means (of MPCI)

Level	N	f	d
1	0.5883	0.5417	0.6337
2	0.5503	0.5833	0.5833
3	0.7083	0.7170	0.6250
Delta	0.1580	0.1753	0.0503
Rank	2	1	3

Delta: (Maximum-Minimum)

Chapter 6
ANFIS based Prediction Modeling

6.1 Coverage

Glass fiber reinforced epoxy comprises high strength to weight ratio, toughness, excellent corrosion and thermal resistance over other engineering materials. With increasing applications of GFRP composites; machining and machinability aspects of composites are very important and need to be studied in detail. Effect of process parameters on various machining performance, quality and productivity need to be examined critically.

Surface roughness is an important product quality feature in any machining operation. Attempts were made by pioneer researchers towards prediction-modeling and optimization of surface roughness of a variety of product in various machining operations.

Literature seems rich in addressing issues of surface roughness: modeling, prediction and optimization, mostly in machining conventional metals. Machining aspects of composites have been addressed in literature to a limited extent. To this end present study highlights a case study in machining glass fiber reinforced epoxy composite. Predictive model has been developed using ANFIS to estimate surface roughness for a given set of input parameters. ANFIS utilizes the concept of neural network and fuzzy logic.

Fuzzy logic is an effective technique for the identification and control of complex non-linear systems. Fuzzy logic is particularly attractive due to its ability to solve problems in the absence of accurate mathematical models. The conventional technique to model the surface roughness results in significant discrepancies between simulation results and experimental data. Artificial Neural Networks (ANNs) have been widely used for modeling complex manufacturing process due to their learning and generalization capabilities, accommodation of non-linear variables, adaptively to changing environments and resistance to missing data. **Jang (1993)** applied ANN in surface roughness study and correlated surface roughness with cutting vibrations. ANNs have been widely applied in modeling different metal cutting operations, such as turning, milling and drilling. The knowledge and the pattern are difficult to learn by the neural network. But fuzzy logic models are easy to cover because they use linguistic terms in the form of IF-THEN rules. A neural network with their learning capabilities can be used to learn the fuzzy decision rules, thus creating a hybrid intelligent system. The fuzzy system provides expert knowledge to be used by the neural network. A fuzzy inference system consists of three components. First, a rule base contains a selection of fuzzy rules. Second, a database defines the membership functions used in the rules and, finally, a reasoning mechanism to carry out the inference procedure on the rules and given facts. This combines the advantageous characteristics of neural network and fuzzy system.

Jiao et al. (2004) used fuzzy adaptive network to model surface roughness in turning operation. A neural fuzzy system was used to predict surface roughness in milling operations **(Chen and Savage, 2001; Lou and Chen, 1999)**. A compound fuzzy inference neural network was used for cutting process online monitoring **(Lin et al. 2002)**. **Jang (1993)** proposed a combination of a neural network and fuzzy logic, called an adaptive neuro-fuzzy inference system. ANFIS is a fuzzy inference system implemented in the model of neural networks. A machining process has been modeled in the present study using ANFIS to predict the effect of machining variables like speed, feed and depth of cut on material removal rate (MRR) and surface finish of the machined composite product. The procedural hierarchy for ANFIS modeling towards prediction of MRR and surface roughness has been shown in **Fig. 6.1**. The details of ANFIS have already been discussed in **Chapter 2**, **Section 2.7**.

6.2 Experimentation

Glass fiber reinforced epoxy composite (fiber orientation 90^0) (E-glass: R099 1200 P556) has been selected as work piece material. Above mat consisted of an E-glass with 72.5 GPa modulus and density of 2590 kg/m^3. Straight turning operation has been performed on aforesaid composite specimens on PINACO lathe. In the present experimental part, spindle speed (N, rpm), feed rate (f, mm/min) and depth of cut (d, mm), have been selected as design factors while other parameters have been assumed to be constant over the experimental domain. The process variables (design factors) with their values at different levels have been listed in **Table 6.1**. The ISO specification of the tool holder used for the turning operation is a WIDAX tool holder PC LNR 2020 K12 and the tool insert used for the study are carbide K-20, (CNMA 120408). A 3-factor-3-level full factorial design **(Table 6.2)** has been used in this experiment. Corresponding to each experimental run, data on MRR and roughness average of the machined work piece have been collected. The experimental layout and the collected response data are shown in **Table 6.2**. Experimental data have been utilized for prediction-modeling of output responses. Representative snaps of machining of glass fiber reinforced epoxy composite have been given in **Appendix 8**.

6.3 Data Analysis and Results

6.3.1 Prediction-Modeling for Surface Roughness

In this part an ANFIS based prediction model has been established for roughness average of finished composite product for machining of glass fiber reinforced epoxy composites. The whole experimental data set has been divided into training set, testing set and checking data set. A total of 27 data sets as shown in **Table 6.2** have been used. Among 27 data, 21 have been considered as training data and 6 as testing data. The **Fig. 6.2** shows the procedure for developing the ANFIS model. During training, a five layered ANFIS model has been constructed as discussed. The number of nodes in the second layer has been increased gradually during training starting with two. It has been observed that the error has converged (decreasing) by increasing the nodes up to three. Hence, the number of nodes in second layer has been set fixed to three and further analysis has been carried out. The five layers have been known as one input, three hidden and one output layer. Three Gaussian type membership functions (guessmf) has been chosen for input as shown in **Figs. 6.3-6.5** and constant type membership function has been used for output during generating FIS. After that 6 data have been used for testing to verify the accuracy of the proposed model. The generated model structure of ANFIS has been shown in **Fig. 6.6**.

The pattern of variation of actual and predicted data has been shown in **Figs. 6.7-6.8**. The blue dots indicate actual output data and red dots represent predicted data. The plots show the coherence nature of the data distribution. The surface plot has been shown in **Fig. 6.9**. It can be observed that the surface covers the total landscape of decision space. A sample set of rule generation for prediction of surface roughness has been shown in **Fig. 6.10**. The on-line predicted surface roughness by ANFIS has an average percent error of 9% when a Gaussian membership function has been applied. This achieves an accuracy of prediction of 91%. ANFIS technique in parallel with power spectrum analysis can be used efficiently to predict the surface roughness on-line during turning process. The objective of improving the surface roughness is to eliminate the discrepancies thus reduces the defective rate of the finished part and thereby, increasing product quality.

6.3.2 Prediction-Modeling for MRR

In this part an ANFIS based prediction model has been established for material removal rate for machining of glass fiber reinforced epoxy composites.

The first and the fourth layer are the adaptive layers in ANFIS. The parameters in the first layer are called premise parameters and consequent parameters in the fourth layer. The least square method is used to optimize the consequent parameter with the premise parameters fixed. The Gradient descent method is used to adjust optimally the premise parameter corresponding to the fuzzy sets in input domain. The output is calculated with the help of consequent parameters.

For anticipating MRR, training database with respect to cutting parameters is necessary to build in an ANFIS. A total set of 21 has been taken for training in ANFIS from the set of 27 dataset obtained from the experiment shown in **Table 6.3**. The training data are responsible for membership function parameters. The training data does not represent the overall features of the presented model due to the data taken during the noisy environment. So, it is necessary to validate the FIS by testing the data set. The testing data is useful in checking the generalization capability of the Fuzzy inference system. The 6 dataset from the aforesaid 27 dataset has been taken for testing to verify the accuracy of the predicted values of MRR shown in **Table 6.3**. In this model N, f, d has been taken as the inputs and MRR has been considered as the output. Gaussian membership function has been used for both the input and output variables shown in **Fig. 6.11**. The number of fuzzy rules in a fuzzy system is related to the number of fuzzy sets for each input variables and the 3 inputs are classified into 3 fuzzy sets. Therefore, maximum number of rules for this model becomes 27 as shown in **Fig. 6.12**.

The pattern of variation of actual and predicted data has been shown in **Figs. 6.13-6.14**. The blue dots indicate actual output and red dots represents predicted data. The plots exhibit the coherence nature of the data distribution. The surface plot has been shown in **Fig. 6.15**. It can be observed that the surface covers the total landscape of decision space. The predicted MRR by ANFIS has an average percent error of 7% when a Gaussian membership function is applied. This achieves an accuracy of prediction of 93%. The objective of improving the roughness and MRR of the surface to eliminate the discrepancies thus reduces the defective rate of the finished part and increasing the quality and productivity.

6.4 Concluding Remarks

In the present work the non-traditional academic architecture adaptive-network based fuzzy inference system (ANFIS) based prediction-modeling has been attempted for analyzing material removal rate as well as surface roughness of machined glass fiber reinforced epoxy composites. ANFIS network reduced the tedious simulation process which includes mesh generation, mesh refinement as well as the computation time. From the investigation, it proves that ANFIS could supply a useful optimal soft computing approach in the composite machining category.

Table 6.1 Process parameters and domain of experiment

Sl. No.	*Factors/process parameters*	*Notation*	*Unit*	*Level 1*	*Level 2*	*Level 3*
1	Cutting speed	N	RPM	360	530	860
2	Feed rate	f	mm/rev	0.083	0.166	0.331
3	Depth of cut	d	mm	2	3	4

Table 6.2 Design of Experiment and collected response data

Exp. No.	*Design of Experiment*			*Response Data*		*Utilization of data for ANFIS modeling*
	N (RPM)	*F (mm/rev)*	*D (mm)*	$R_{a(avg)}$ *(μm)*	*MRR* *(mm^3/min)*	
1	360	0.083	2	6.533	3822.921	Training Data
2	360	0.083	2	5.5733	4360.385	
3	360	0.083	2	5.2	13092.62	
4	360	0.166	3	7.733	14639.08	
5	360	0.166	3	7.966	15817.12	
6	360	0.166	3	7.84	33812.12	
7	360	0.331	4	9.466	28669.59	
8	360	0.331	4	9.63	11502.97	
9	360	0.331	4	11.133	9560.534	
10	530	0.083	3	7.2	25364.91	
11	530	0.083	3	7	22683.2	
12	530	0.083	3	6.92	31499.49	
13	530	0.166	4	6.333	30503.99	
14	530	0.166	4	5.166	34800.87	
15	530	0.166	4	5.4	23945.86	
16	530	0.331	2	6.92	21678.33	
17	530	0.331	2	6.88	16302.09	
18	530	0.331	2	6.86	27904.81	
19	860	0.083	4	7.033	22042.64	
20	860	0.083	4	6.84	75021.07	
21	860	0.083	4	6.9	75401.89	Testing Data
22	860	0.166	2	5.8667	4831.638	
23	860	0.166	2	6	41518.68	
24	860	0.166	2	6.2	11316.03	
25	860	0.331	3	9.3	29397.13	
26	860	0.331	3	10.2	22861.52	
27	860	0.331	3	9.54	69367	

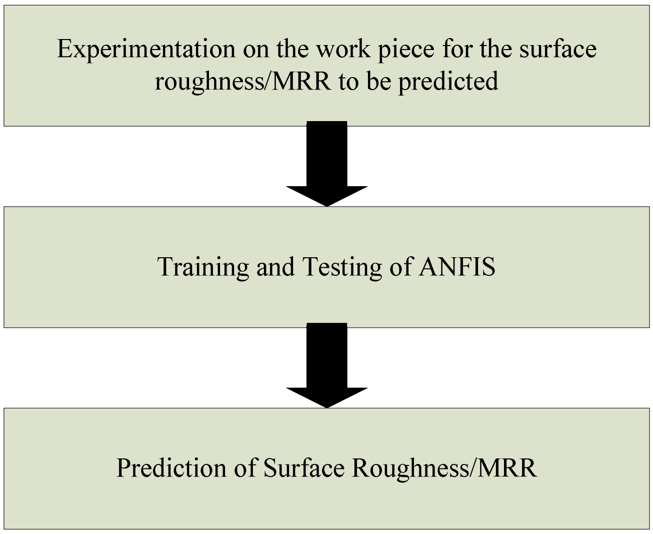


Figure 6.1: Development of ANFIS-model for surface roughness/MRR prediction

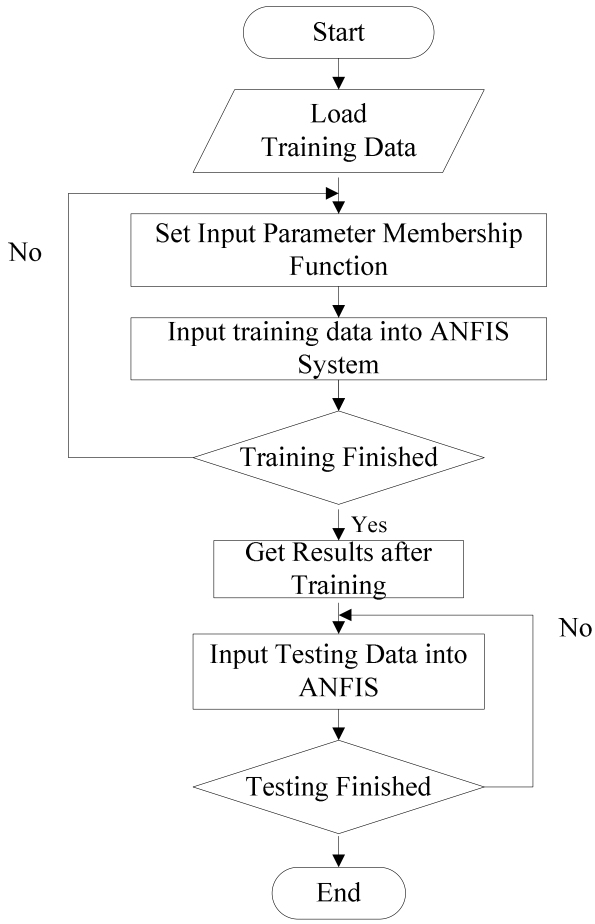


Figure 6.2: Flow chart of establishing ANFIS model

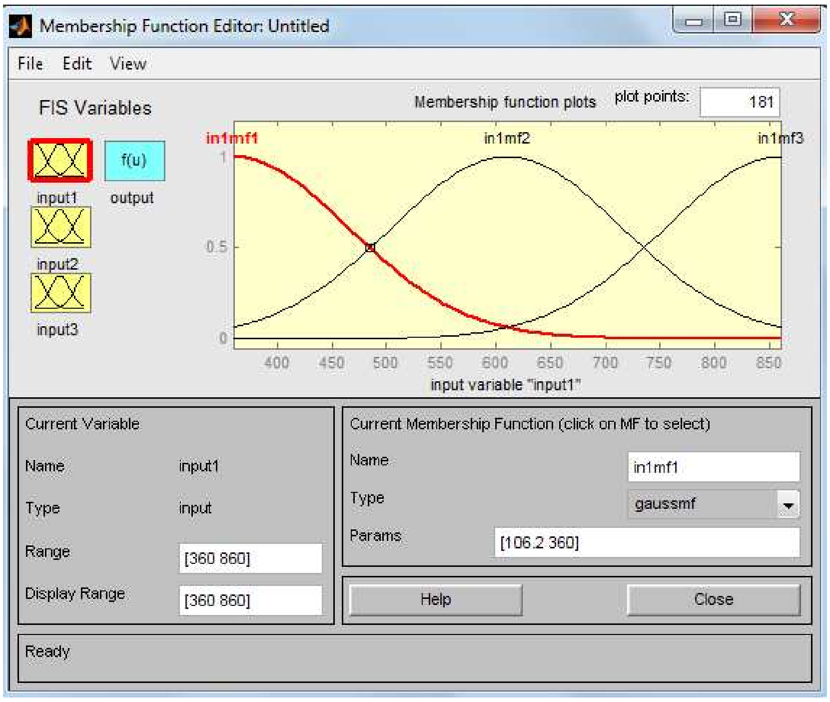


Figure 6.3: Membership function for input1

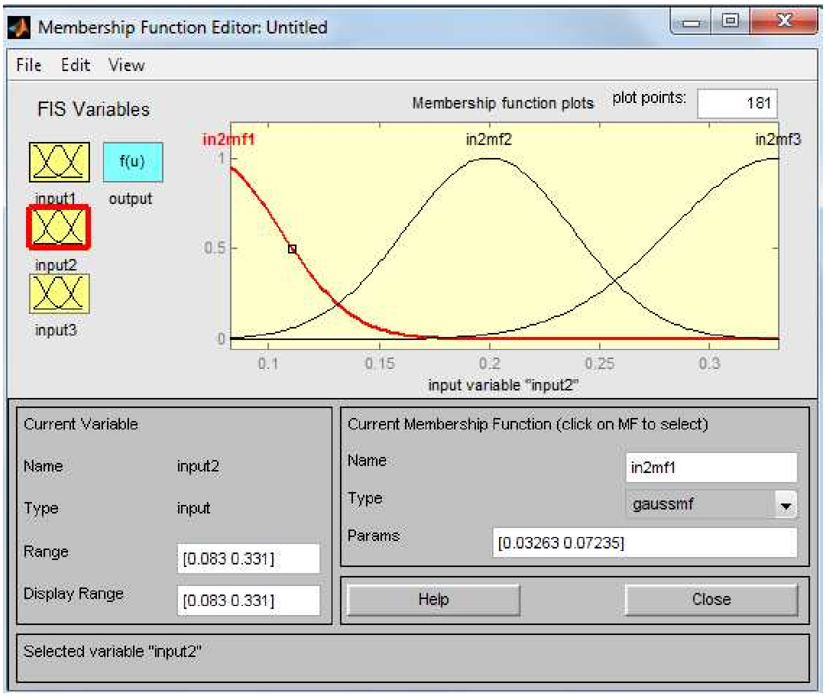


Figure 6.4: Membership function for input2

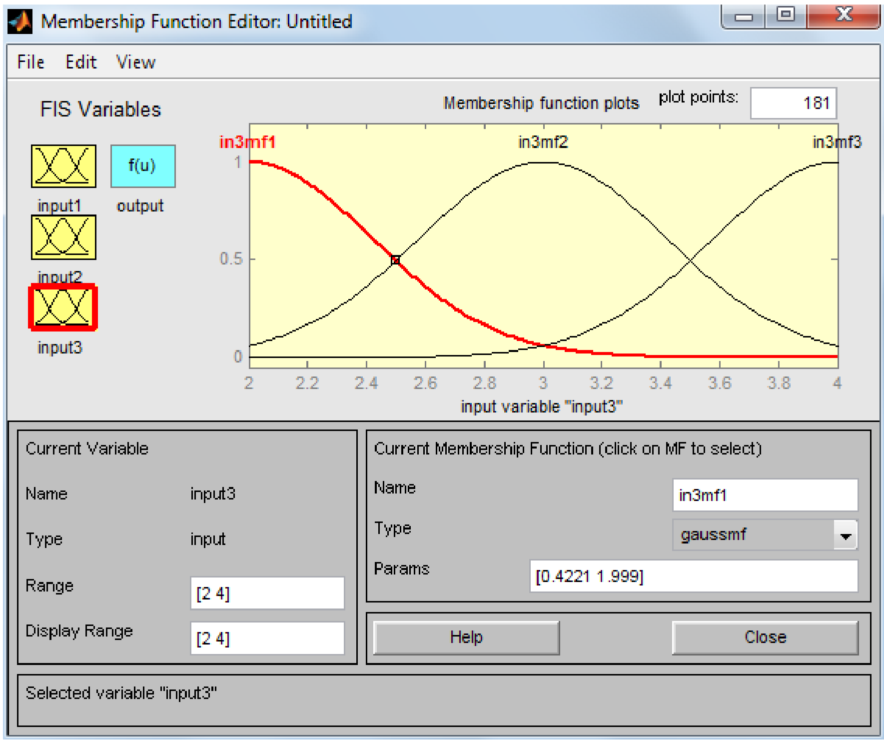


Figure 6.5: Membership function for input3

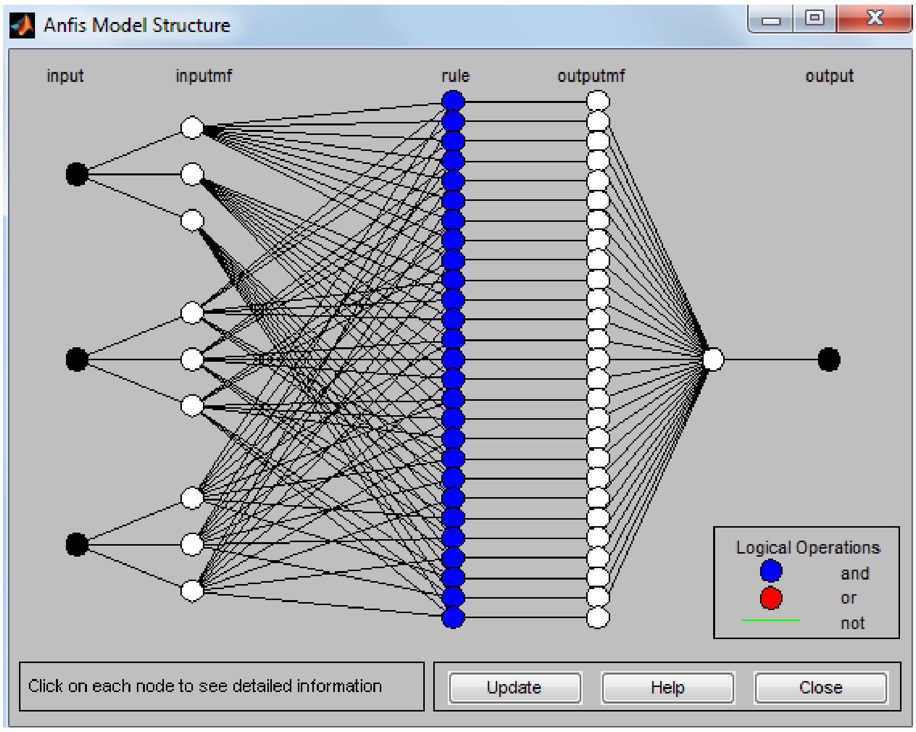


Figure 6.6: ANFIS-model for surface roughness/MRR prediction

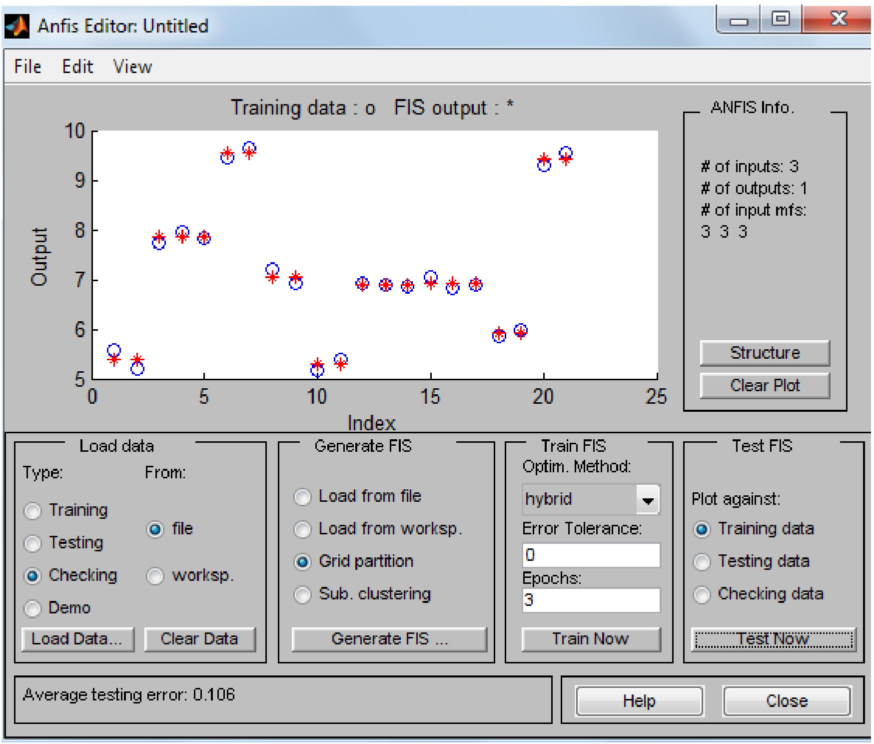


Figure 6.7: Distribution of actual and predicted data of surface roughness (training)

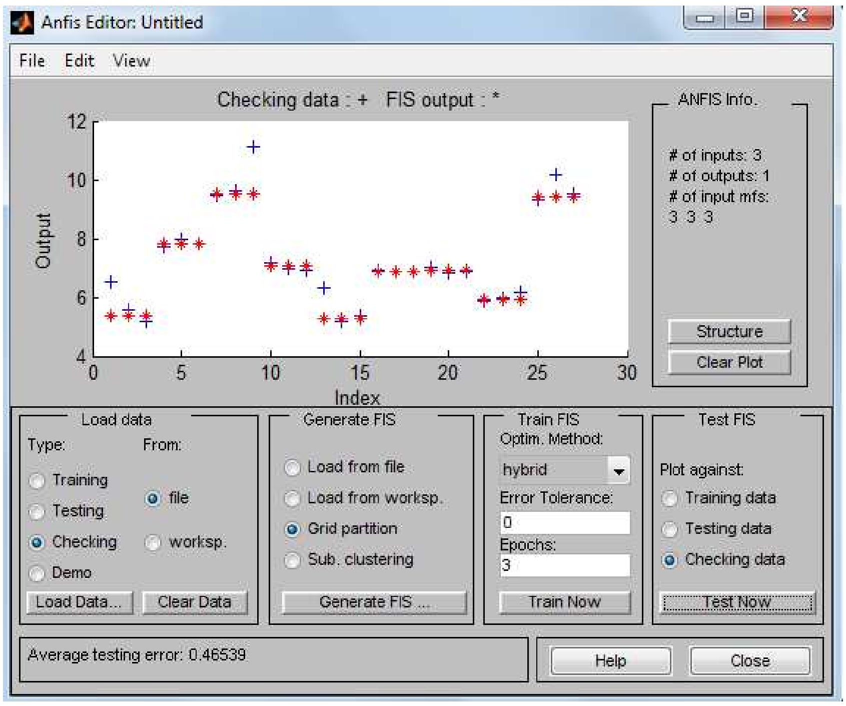


Figure 6.8: Distribution of actual and predicted data of surface roughness (testing)

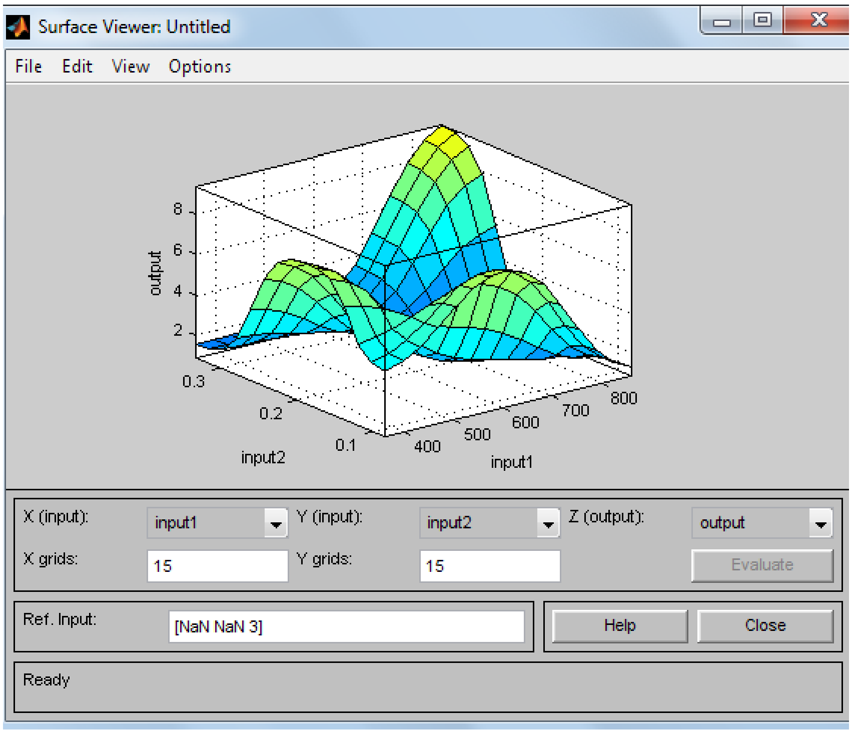


Figure 6.9: The surface plot for predicting surface roughness

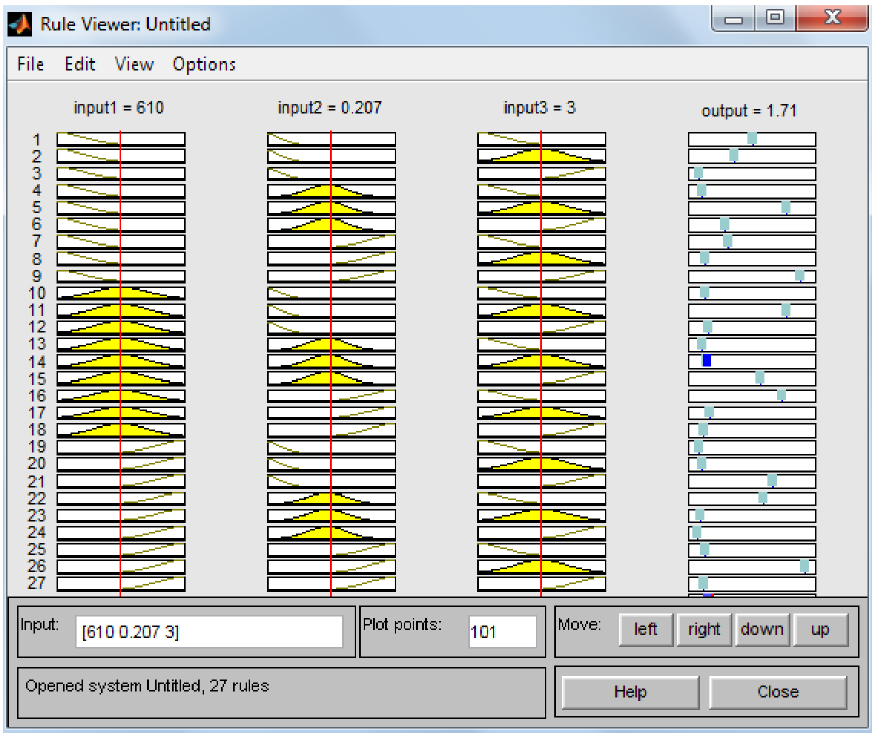


Figure 6.10: A sample set of rules for prediction of surface roughness

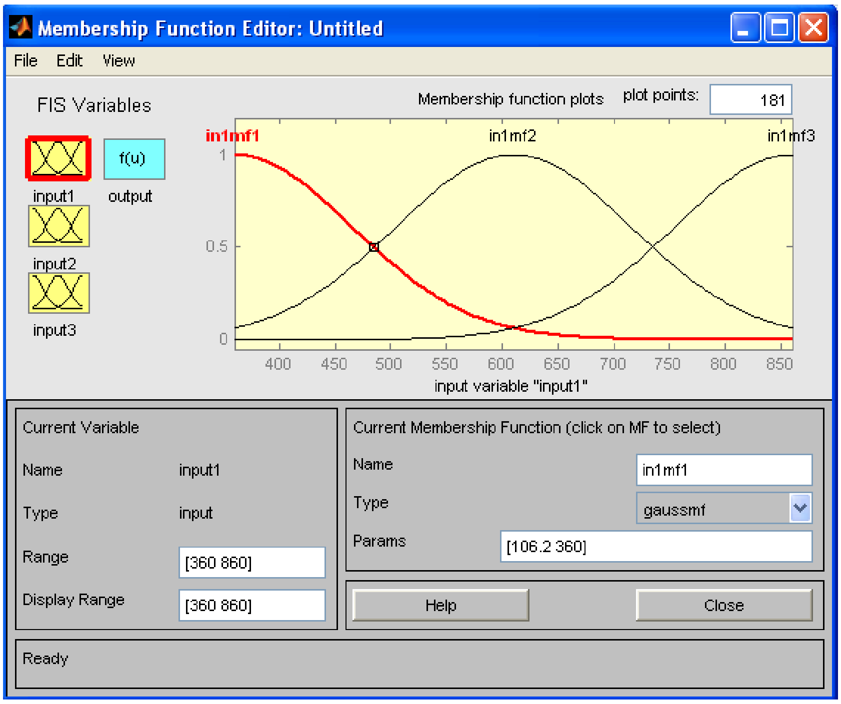


Figure 6.11: Membership function for input(s) and output

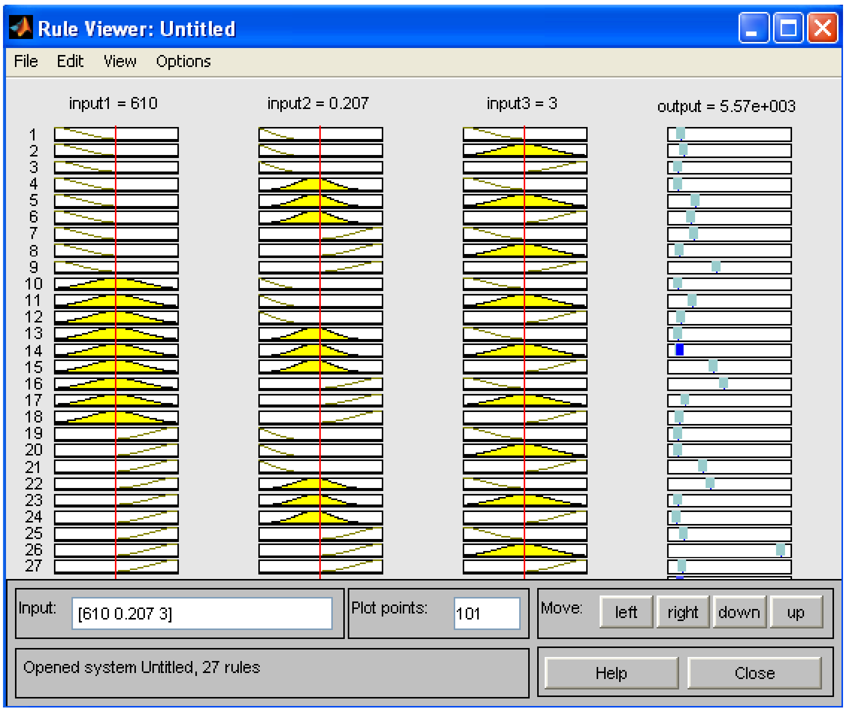


Figure 6.12: A sample set of rules for prediction of MRR

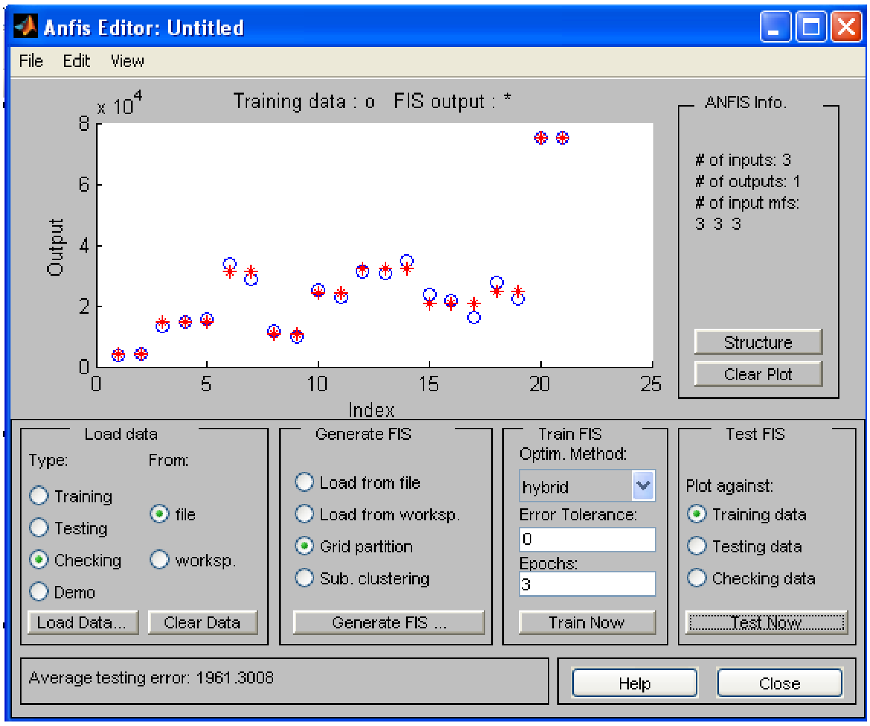


Figure 6.13: Distribution of actual and predicted data of MRR (training)

Figure 6.14: Distribution of actual and predicted data of MRR (testing)

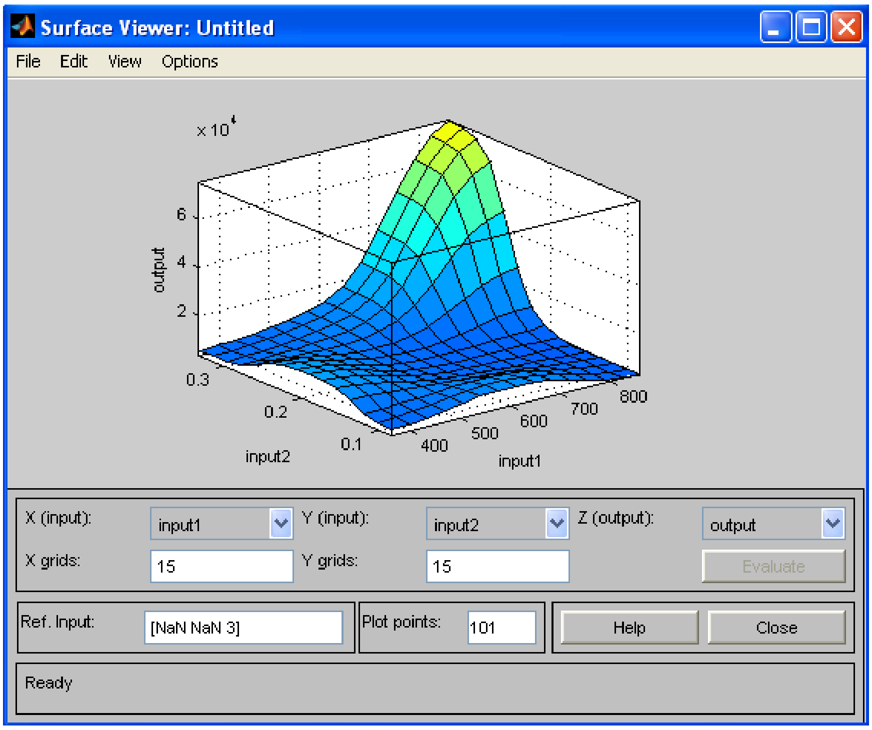


Figure 6.15: The surface Plot for predicting MRR

Chapter 7
Conclusion and Scope for Future Work

7.1 Conclusion

In the foregoing study, detailed investigation emphasizing process modeling along with multi-response optimization has been attempted followed by a case study in composite machining.

Glass fiber reinforced polymers offer excellent machining properties in comparison with conventional engineering materials. It has been revealed that various machining parameters have certain degree of influence on surface roughness and material removal rate (MRR) during machining operation. Quality and productivity are two important aspects of concern in manufacturing/production industries. Improving quality-productivity by reducing cost and increasing the performance of machine tools are indeed the challenging aspects in manufacturing industries to survive competitively in the global marketplace. In general, among different controllable process variables which are responsible in affecting process performances i.e. process- responses (output); it is indeed very difficult to find the best optimal parameter settings.

The thesis aims to search the best process environment; simultaneously satisfying conflicting requirements of process responses. Traditional, hybrid optimization methodologies have been applied to search satisfactory results. The objectives of the thesis have been established considering the scope in overcoming the limitations and trends of the single objective optimization documented in literature.

In **Chapter 3** application of TOPSIS based Taguchi method has been adopted to optimize multiple surface roughness parameters of machined GFRP polyester composites. The concept of this method is to select the alternative that have the shortest distance from the positive ideal solution and the farthest distance from negative ideal solution. Positive ideal solution is a solution that maximizes the benefit criteria and minimizes cost criteria, whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria.

The above methodology explains the cost and time consuming effects which create errors. So, it is necessary that the primary function of one intelligent technique is replaced by the primary function of another intelligent technique to increase quality and productivity.

Application of desirability function, utility theory and fuzzy based Taguchi optimization method has been presented in **Chapter 4**. Literature reveals that Taguchi approach fails to solve multi-objective optimization problems. Various methodologies like desirability function, utility theory, and grey theory have been attempted by previous researchers to find the optimal condition but improper assignment of response weight and existence of correlation among the responses may yield erroneous results. To avoid those limitations fuzzy logic has been integrated with the aforesaid optimization philosophies.

In order to eliminate response correlation, application of PCA- fuzzy based Taguchi method has been explained in **Chapter 5**. Principal Component Analysis (PCA) is one of the most useful statistical techniques for examining the relationships within a given data set of multiple-performance-characteristics. A new set of uncorrelated data, called principal components (PCs) can be derived by PCA in descending order of their ability to explain the variance of the original dataset. This uncorrelated quality responses are to be fed in Fuzzy Inference System (FIS) to compute MPCI. MPCI is to be optimized by Taguchi method.

Chapter 6 shows one of the latest techniques i.e. application of ANFIS based prediction modeling. The knowledge and the pattern are difficult to learn by the neural network. But fuzzy logic models are easy to cover because they use linguistic terms in the form of IF-THEN rules. A neural network with their learning capabilities can be used to learn the fuzzy decision rules, thus creating a hybrid intelligent system i.e. ANFIS. The fuzzy system provides expert knowledge to be used by the neural network. An efficient mathematical approach for the calculation of quality and productivity indicator factors in turning operations has been studied. Surface roughness average (R_a), R_q (root mean square roughness), R_t (Maximum Height of Profile) , R_{sm} (Mean width of profile elements), R_{ku} (Kurtosis of the roughness profile), R_z (Average Maximum Height of the Profile) and material removal rate (MRR) are calculated as function of depth of cut, feed rate, cutting speed.

The methodologies for prediction as well as optimization has been presented, the theoretical studies on the surface roughness generation and the material removal rate would permit machine tool operators to optimize the parameter selection, maximizing productivity while ensuring quality requirements.

When a single set of experimentally measured data is analyzed by a number of computational techniques with a unified aim (such as providing a set of optimum process conditions), it is felt necessary to deliver a discussion and subsequent conclusion on the relative performance/measure of the techniques that are used. To answer this, it is very difficult to conclude firmly on relative performance of the optimization philosophies presented. It is very difficult to say which technique is the most efficient. It mainly depends on the Decision-Maker (DM). The DM should decide how many objective functions need to be considered, what will be the response priority weight? Whether response correlation is to be considered or not? Moreover, depending of the application area and functional requirements of the product, DM should think on criteria requirements (Higher-the-Better/Lower-the-Better/Target-is-the-Best). The objective of the thesis is to modify existing optimization philosophies to overcome inherent assumptions as well as modifications. For example, TOPSIS/DF Approach/Utility Theory combined with Taguchi method can be applied for uncorrelated multi-response optimization; whereas PCA/FIS based Taguchi method can be used to optimize multiple correlated responses simultaneously. Therefore, it is managerial decision (discretion of the Decision-Making group) towards selecting a particular optimization tool/technique.

The main contributions of this research have been summarized below.

1. Development of PCA-Fuzzy-Taguchi integrated multi-objective optimization procedural hierarchy applicable for continuous quality-productivity improvement and off-line quality control in any manufacturing/production processes.
2. The proposed multi-objective optimization module is capable of overcoming limitations/assumptions those are inherent in traditional Taguchi based optimization techniques documented in literature.
3. Exploration of Fuzzy Inference System (FIS) avoids possibility of imprecision, inaccuracy of prediction generally caused by improper assignment of response weights, and existence of inter-correlation among output responses.
4. ANFIS modeling reveals behavioral scenario of process input parameters in relation with output responses.

7.2 Scope for Future Work

The limitations of this research are as follows:

1. Interaction effect of process parameters has been neglected.
2. The composite with random fiber orientation has been studied only.
3. Variation of tool geometry, tool material has not been considered.
4. Effect of machine tool vibration has been ignored.

Some future directions of this research are as follows:

1. Investigation on machining of composites with a variety of fiber orientation.
2. Aspects of tool life/tool wear have to be investigated. In any kind of machining process, another aspect of great concern is the tool life. Lesser extent of tool wear and increased tool life is always preferred. The present work highlights quality-productivity optimization in machining GFRP composites. Surface roughness values have been considered as the product quality measure; and MMR has been interpreted as productivity estimate. As tool life is not directly related to quality-productivity; therefore, this aspect has not been considered/included in the list of objective functions.
3. Apart from turning, other machining processes like milling, drilling etc. need to be carried out on composite materials.
4. Dimensional accuracy, extent tool wear may be included in the list of objective functions.
5. Apart from triangular fuzzy membership function, trapezoidal MFs may be explored.

Bibliography

1. M. Rahman, S. Ramakrishna, J.R.S. Prakash, D.C.G. Tan, Machinability study of carbon fiber reinforced composite, Journal of Materials Processing Technology, 89-90 (1999) 292-297.
2. J. R. Ferreira, N.L. Coppini, G.W.A. Miranda, Machining Optimisation in Carbon Fibre Reinforced Composite Materials, Journal of Materials Processing Technology, 92-93 (1999) 135-140.
3. E. Ugo. Enemuoh, A. Sherif El-Gizawy, A. Chukwujekwu Okafor, An Approach for Development of Damage-Free Drilling of Carbon Fiber Reinforced Thermosets, International Journal of Machine Tools and Manufacture, 41 (12) (2001) 1795-1814.
4. J. Paulo Davim, Pedro Reis, C. Conceição António, Experimental Study of Drilling Glass Fiber Reinforced Plastics (GFRP) Manufactured by Hand Lay-Up, Composites Science and Technology, 64 (2) (2004) 289-297.
5. I. El-Sonbaty, U.A. Khashaba, T. Machaly, Factors Affecting the Machinability of GFR/Epoxy Composites, Composite Structures, 63 (2004) 329–338.
6. J. Paulo Davim, F. Mata, Optimisation of Surface Roughness on Turning Fibre-Reinforced Plastics (FRPs) with Diamond Cutting Tools, International Journal of Advanced Manufacturing Technology, 26 (2005a) 319–323.
7. J. Paulo Davim, F. Mata, A New Machinability Index in Turning Fiber Reinforced Plastics, Journal of Materials Processing Technology, 170 (1-2) (2005b) 436-440.
8. R. Zitoune, F. Collombet, F. Lachaud, R. Piquet, P. Pasquet, Experiment–Calculation Comparison of the Cutting Conditions Representative of the Long Fiber Composite Drilling Phase, Composites Science and Technology, 65 (3-4) (2005) 455-466.

9. E. Bagci, B. Işık, Investigation of Surface Roughness in Turning Unidirectional GFRP Composites by Using RS Methodology and ANN, International Journal of Advanced Manufacturing Technology, 31 (2006) 10–17.

10. J. Paulo Davim, F. Mata, New Machinability Study of Glass Fibre Reinforced Plastics Using Polycrystalline Diamond and Cemented Carbide (K15) Tools, Materials and Design, 28 (3) (2007) 1050-1054.

11. C.C. Tsao, H. Hocheng, Evaluation of Thrust Force and Surface Roughness in Drilling Composite Material Using Taguchi Analysis and Neural Network, Journal of Materials Processing Technology, 203 (1-3) (2008) 342-348.

12. J. Campos Rubio, A.M. Abrao, P.E. Faria, A. Esteves Correia, J. Paulo Davim, Effects of High Speed in the Drilling of Glass Fibre Reinforced Plastic: Evaluation of the Delamination Factor, International Journal of Machine Tools and Manufacture, 48 (6) (2008) 715-720.

13. Jamal Sheikh-Ahmad, R. Yadav, Model for Predicting Cutting Forces in Machining CFRP, International Journal of Materials and Product Technology, 32 (2-3) (2008) 152-167.

14. J. Paulo Davim, Leonardo R. Silva, António Festas, A.M. Abrão, Machinability Study on Precision Turning of PA66 Polyamide With and Without Glass Fiber Reinforcing, Materials and Design, 30 (2009) 228–234.

15. M. K. A Mohd Ariffin, M. I. Mohd Ali, S. M. Sapuan, N. Ismail, An Optimised Drilling Process for an Aircraft Composite Structure Using Design of Experiments, Scientific Research and Essay, 4 (10) (2009) 1109-1116.

16. António T. Marques, Luís M. Durão, António G. Magalhães, João Francisco Silva, João Manuel R.S. Tavares, Delamination Analysis of Carbon Fibre Reinforced Laminates:

Evaluation of a Special Step Drill, Composites Science and Technology, 69 (14) (2009) 2376-2382.

17. F. Mata, E. Beamud, I. Hanafi, A. Khamlichi, A. Jabbouri,, M. Bezzazi, Multiple Regression Prediction Model for Cutting Forces in Turning Carbon-Reinforced PEEK CF30, Advances in Materials Science and Engineering, 2010 (2010), Article ID 824098, 7 pages, doi:10.1155/2010/824098.
18. G. Santhanakrishnan, R. Krishnamurthy, S.K. Malhotra, Machinability Characteristics of Fibre Reinforced Plastics Composites, Journal of Mechanical Working Technology, 17 (1988) 195 – 204.
19. K.L. Palanikumar, R. Karunamoorthy, Kartikeyan, Optimizing of Machining Parameters for Minimum Surface Roughness in Turning of GFRP Composites using Design of Experiments, Journal of Materials Processing Technology, 20 (4) (2004) 373-378.
20. N.S. Mohan, A. Ramachandra, S.M. Kulkarni, Influence of Process Parameters on Cutting Force and Torque during Drilling of Glass–Fiber Polyester Reinforced Composites, Composite Structures, 71 (2005) 407–413.
21. N. Dayananda Jawali, B. Siddeswarappa, Siddaramaiah, Physicomechanical Properties, Machinability, and Morphological Behavior of Short Glass Fiber-reinforced Nylon 6 Composites, Journal of Reinforced Plastics and Composites, 25 (13) (2006) 1409-1418.
22. K. Palanikumar, L. Karunamoorthy, R. Karthikeyan, Assessment of Factors Influencing Surface Roughness on the Machining of Glass Fiber-Reinforced Polymer Composites, Materials and Design, 27 (2006) 862–871.
23. K. Palanikumar, J. P. Davim, Mathematical Model to Predict Tool Wear on the Machining of Glass Fiber Reinforced Plastic Composites, Materials and Design, 28 (2007) 2008–2014.

24. K. Palanikumar, Modeling and Analysis for Surface Roughness in Machining Glass Fibre Reinforced Plastics Using Response Surface Methodology, Materials and Design, 28 (2007) 2611–2618.

25. S.R. Karnik, V.N. Gaitonde, Francisco Mata, J. Paulo Davim, Investigative Study on Machinability Aspects of Unreinforced and Reinforced PEEK Composite Machining using ANN Model, Journal of Reinforced Plastics and Composites, 27 (7) (2008) 751-768.

26. K. Palanikumar, Application of Taguchi and Response Surface Methodologies for Surface Roughness in Machining Glass Fiber Reinforced Plastics by PCD Tooling, International Journal of Advanced Manufacturing Technology, 36 (2008a) 19–27.

27. Abeesh C. Basheer, Uday A. Dabade, Suhas S. Joshi, V.V. Bhanuprasad, V.M. Gadre, Modeling of Surface Roughness in Precision Machining of Metal Matrix Composites using ANN, Journal of Materials Processing Technology, 197 (2008) 439–444.

28. K. Palanikumar, F. Mata, J. Paulo Davim, Analysis of Surface Roughness Parameters in Turning of FRP Tubes by PCD Tool, Journal of Materials Processing Technology, 204 (2008) 469–474.

29. K. Palanikumar, 2008b, Surface Roughness Model for Machining Glass Fiber Reinforced Plastics by PCD Tool using Fuzzy Logics, Journal of Reinforced Plastics and Composites, Vol. 00, No. 00/2008 1-14. DOI: 10.1177/0731684408092009.

30. V. Krishnaraj, Effect of Drill Points on Glass Fibre reinforced Plastics Composites while Drilling at High Spindle Speed, Proceedings of the World Congress on Engineering, Volume II, WCE 2008, July 2-4, 2008, London, U.K.

31. A. Naveen Sait, S. Aravindan, A. Noorul Haq, Optimization of Machining Parameters of Glass Fiber Reinforced Plastic (GFRP) Pipes by Desirability Function Analysis using

Taguchi Technique", International Journal of Advance Manufacturing Technology, 43 (2009) 581-589.

32. K. Palanikumar, J. P. Davim, Assessment of Some Factors Influencing Tool Wear on the Machining of Glass Fiber Reinforced Plastics by Coated Cemented Carbide Tools, Journal of Materials Processing and Technology, 209 (2009) 511–519.
33. R. Vimal Sam Singh, B. Latha, V.S. Senthikumar, Modeling and Analysis of Thrust Force and Torque in Drilling GFRP Composites by Multi-Facet Drill Using Fuzzy Logic, International Journal of Recent Trends in Engineering, 1 (5) (2009) 66-70.
34. S.A. Hussain, V. Pandurangadu, K. Palanikumar, Surface Roughness Analysis in Machining of GFRP Composites by Carbide Tool (K20), European Journal of Scientific Research, 41 (1) (2010) 84-98.
35. T. Rajasekaran, K. Palanikumar, B.K. Vinayagam, Application of Fuzzy Logic for Modeling Surface Roughness in Turning CFRP Composites Using CBN Tool, Production Engineering and Research Development, 5 (2011) 191-199.
36. G. Spur, U.E. Wunsch, Turning of fiber-reinforced plastics, Manuf Rev, (1998), 1(2) 124–129.
37. O.B. Abouelatta, J. M´adl, Surface roughness prediction based on cutting parameters and tool vibrations in turning operations. Journal of Materials Processing Technology, 118(2001) 269–277.
38. E. Erisken, Influence from production parameters on the surface roughness of a machine short fibre reinforced thermoplastic, International Journal of Machine Tools and Manufacture, 39(1999) 1611–1618.
39. F. Mata, J.P. Davim, An investigation about the precision turning fiber reinforced plastics (FRP's) with diamond cutting tools using multiple analysis regression. II Iberian Conference of Tribology, (2003), Valencia, pp. 117–124.

40. S. Jahanmir, M. Ramulu, P. Koshy, Machining of ceramics and composites. Dekker, New York, (1998) 238–243.

41. V.K. Jain, S.K. Choudhury, K.M. Ramesh, On the machining of alumina and glass, International Journal of Machine Tools and Manufacture, 42(2002) 1269–1276.

42. J.P. Davim, Silva Leonardo R, F. António, A.M. Abrão, Machinability study on precision turning of PA66 polyamide with and without glass fiber reinforcing, Materials and Design, 30(2009) 228–34.

43. M.H. Geier, Quality handbook for composite materials. Chapman & Hall Publications; 1994.

44. E.S. Lee, Precision machining of glass fibre reinforced plastics with respect to tool characteristics, International Journal of Advanced Manufacturing Technology, 17(2001) 791–8.

45. L.C. Zhang, Cutting composites: a discussion on mechanics modeling, Journal of Materials Processing Technology, 209(2009) 4548–52.

46. G. Santhanakrishnan, R. Krishnamurthy, S.K. Malhotra, High speed tool wear studies in machining of glass fibre reinforced plastic, Wear, 132(1989) 327–336.

47. N. Bhatnagar, N. Ramakrishnan, N.K. Naik, R. Komanduri, On the machining of fibre reinforced plastic (FRP) composite laminates, International Journal of Machine Tools and Manufacture, 35(5)(1995) 701–16.

48. Venu Gopala Roa G, P. Mahajan, N. Bhatnagar, Machining of UD—GFRP composites chip formation mechanism, Composites Science and Technology, 67(2007) 2271–81.

49. M. Sharma, I.M. Rao, J. Bijwe, Influence of orientation of long fibers in carbon fiber–polyetherimide composites on mechanical and tribological properties, Wear, 267(2009) 839–45.

50. P.S. Sreejith, R. Krishnamurthy, S.K. Malhotra, Effect of specific cutting pressure and temperature during machining of carbon/phenolic ablative composite using PCBN tools, Journal of Materials Processing Technology, 183(2007) 88–95.
51. Syed Altaf Hussain, V. Pandurangadu, K. Palanikumar, Surface Roughness Analysis in Machining of GFRP Composites by Carbide Tool (K20), European Journal of Scientific Research, 41(1)(2010) 84-98.
52. P. Sahoo, Engineering Tribology, Prentice Hall of India, New Delhi, 2005.
53. S. Datta, A. Bandyopadhyay, P.K. Pal, Application of Taguchi Philosophy for Parametric Optimization of Bead Geometry and HAZ Width in Submerged Arc Welding Using Mixture of Fresh Flux and Fused Slag, International Journal of Advanced Manufacturing Technology, 36 (2008a) 689-698.
54. S. Datta, A. Bandyopadhyay, P.K. Pal, Grey Based Taguchi Method for Optimization of Bead Geometry in Submerged Arc Bead-On-Plate Welding, International Journal of Advanced Manufacturing Technology, 39 (2008b) 1136-1143.
55. G. Derringer, *R.* Suich, Simultaneous optimization of several response variables, Journal of Quality Technology, 12 (4) (1980) 214-219.
56. S. Datta, A. Bandyopadhyay, P. K. Pal, Desirability Function Approach for Solving Multi-Objective Optimization Problem in Submerged Arc Welding, International Journal for Manufacturing Science and Production, 7(2) (2006) 127-135.
57. P. Kumar, P. B. Barua, J. L. Gaindhar, Quality Optimization (Multi-Characteristics) Through Taguchi's Technique and Utility Concept, Quality and Reliability Engineering International, 16 (2000) 475-485.
58. R. S. Walia, H. S. Shan, P. Kumar, Multi-Response Optimization of CFAAFM Process through Taguchi Method and Utility Concept, Materials and Manufacturing Processes, 21 (2006) 907-914.

59. S. Datta, G. Nandi, A. Bandyopadhyay, Application of Entropy Measurement Technique in Grey Based Taguchi Method for Solution of Correlated Multiple Response Optimization Problems: A Case Study in Welding, Journal of Manufacturing Systems, 28 (2009a) 55-63.
60. C.T. Su, L.I. Tong, Multi-Response Robust Design by Principal Component Analysis, Total Quality Management, 8 (6) (1997) 409-416.
61. S. Datta, G. Nandi, A. Bandyopadhyay, P. K. Pal, Application of PCA based hybrid Taguchi method for multi-criteria optimization of submerged arc weld: A case study, International Journal of Advanced Manufacturing Technology, 45 (3-4) (2009b) 276-286.
62. B. C. Routara, S. D. Mohanty, S. Datta, A. Bandyopadhyay, S. S. Mahapatra, Combined Quality Loss (CQL) concept in PCA based Taguchi philosophy for optimization of multiple surface quality characteristics of UNS C34000 Brass in cylindrical grinding, International Journal of Advanced Manufacturing Technology, 51 (2010) 135-143.
63. Hung-Chang Liao, Multi-Response Optimization Using Weighted Principal Component, International Journal of Advanced Manufacturing Technology, 27 (7-8) (2006) 720-725.
64. D. Lu, J. Antony, Optimization of Multiple Responses Using a Fuzzy-Rule Based Inference System, International Journal of Production Research, 40 (7) (2002) 1613-1625.
65. L.A. Zadeh, Fuzzy-Algorithm Approach to the Definition of Complex or Imprecise Concept, International Journal of Man Machine Studies, 8 (1976) 249-291.
66. J.M. Mendel, Fuzzy Logic Systems for Engineering: A Tutorial, IEEE Proc, 83 (1995) 345-377.
67. E.A. Cox, Fuzzy Fundamentals, IEEE Spectrum, 29 (1992) 58-61.
68. R.R. Yager, D.P. Filev, Essential of Fuzzy Modeling and Control, 1999, John Willey and Sons Inc., New York.

69. P.J. Ross, Taguchi Techniques for Quality Engineering: Loss Function, Orthogonal Experiments, Parameter and Tolerance Design - 2nd ed, New York, NY: McGraw-Hill (1996).
70. M.S. Phadke, Quality Engineering Using Robust Design. Englewood Cliffs, NJ: Prentice-Hall; (1989).
71. W.H. Yang, Y.S. Tarng, Design optimization of cutting parameters for turning operations based on the Taguchi method, Journal of Materials Processing Technology, 84 (1998) 122–129.
72. Y.L. Su, S.H. Yao, C.S. Wei, W.H. Kao , C.T. Wu, Design and performance analysis of TiCN- coated cemented carbide milling cutters, Journal of Materials Processing Technology, 87 (1999) 82–89.
73. C.Y. Nian, W.H. Yang, Y. S. Tarng, Optimization of turning operations with multiple performance characteristics, Journal of Materials Processing Technology, 95 (1999) 90–96.
74. T.R. Lin, Experimental design and performance analysis of TiN coated carbide tool in face milling stainless steel, Journal of Materials Processing Technology, 127 (2002) 1–7.
75. J.P. Davim, Design optimization of cutting parameters for turning metal matrix composites based on the orthogonal arrays, Journal of Materials Processing Technology, 132 (2003) 340–344.
76. J.A. Ghani, I.A. Choudhury , H.H. Hassan, Application of Taguchi method in the optimization of end milling operations, Journal of Materials Processing Technology, 145 (2004) 84–92.
77. C. L. Hwang, K. Yoon, ‘Multiple Attribute Decision Making Methods and Applications’, A State-of-the-Art Survey, Springer Verlag, New York (1981).

78. L.-I. Tong, C.-T. Su, Optimizing multi-response problems in the Taguchi method by fuzzy multiple attribute decision making, Quality and Reliability Engineering International 13 (1997) 25–34.

79. Liao Hung-Chang, Using PCR-TOPSIS to optimize Taguchi's multi-response problem, International Journal of Advanced Manufacturing Technology, 22 (2003) 649-655.

80. Y. Wang, Z. He, A New TOPSIS Based Methodology for Multiple Responses Problem, 8th International Conference on Wireless Communications, Networking and Mobile Computing WiCOM, Dalian (2008).

81. C.T. Su, L.I. Tong, Multi-Response Robust Design by Principal Component Analysis, Total Quality Management, 8 (6) (1997) 409-416.

82. Sivarao, P. Brevern, N.S.M. El-Tayeb, V.C. Vengkatesh, Mamdani fuzzy inference system modeling to predict surface roughness in laser machining. International Journal of Intelligent Information and Technology Application, 2(1) (2009) 12-18.

83. Yi-Chin Fang, Yih-Fong Tzeng, Si-Xiang. Li, A Taguchi PCA fuzzy-based approach for the multi-objective extended optimization of a miniature optical engine Journal of Physics D: Applied Physics, 41(17) (2008) 16.

84. M. Sugeno, G.T. Kang, Structure identification of fuzzy model. Fuzzy Sets System, 28 (1988) 15–33.

85. R. J. Jang, Fuzzy modeling using generalized neural networks and Kalmman filter algorithm. In Proceedings of the ninth national conference on artificial intelligence, (1991) 762–767.

86. R.J. Jang, ANFIS: Adaptive-network-based fuzzy inference system. IEEE Transaction on Systems of Max and Cybernatics, 23(03) (1993) 665–685.

87. J. S. Roger Jang and C. T. Sun, "Neuro-fuzzy modeling and control", Proceedings of the IEEE, 83, pp. 378 –404, 1995.

88. C. L. Hwang, K. Yoon, Multiple Attribute Decision Making Methods and Applications, A State-of-the-Art Survey, Springer Verlag, New York, (1981).
89. T. S. Lan, Taguchi Optimization of multi- objective CNC Machining using TOPSIS, Information Technology Journal, 86 (2009) 917-922.
90. T. Yang, P. Chou, Solving a multiresponse simulation-optimization problem with discrete variables using a multiple-attribute decision-making method, Mathematics and Computers in Simulation,68 (2005) 9-21.
91. E.Angun, G. Gurkan, D. Hertog, J. P. C. Kleijnen, Response surface methodology with stochastic constraints for expensive simulation, Working Paper, Tilburg University, Netherlands, (2003).
92. L.-I. Tong, C.-T. Su, Optimizing multi-response problems in the Taguchi method by fuzzy multiple attribute decision making, Quality and Reliability Engineering International, 13 (1997) 25-34.
93. Y. Wang, Z. He, Optimal Multi-response Problems on the Improved TOPSIS Method, Wireless Communications, networking and Mobile Computing, (2007) 5092-5094.
94. P. Liu, An Extended TOPSIS Method for Multiple Attribute Group Decision Making Based on Generalized Interval-valued Trapezoidal Fuzzy Numbers, Informatica, 35 (2011) 185-196.
95. W. H. Yang, Y. S. Tang, Design optimization of cutting parameters for turning operations based on the Taguchi method, Journal of Material Processing and Technology, 84 (1998) 122-129.
96. H. S. Adeel, N. Ismail, S. V. Wong, J. N.A. Abdul, Optimization of Cutting Parameters Based on Surface Roughness and Assistance of Work piece Surface Temperature in Turning Process, American Journal of Engineering and Applied Sciences, 3 (1) (2010) 102-108.

97. S. A. Hussain, V. Pandurangadu, K. Palanikumar, Surface Roughness Analysis in Machining of GFRP Composites by Carbide Tool (K20), European Journal of Scientific Research, 41 (1) (2010) 84-98.
98. A. Singh, S. Datta, S. S. Mahapatra, T. Singha, G. Majumdar, Optimization of Bead Geometry of Submerged Arc Weld using Fuzzy based Desirability Function Approach, Journal of Intelligent Manufacturing, Springer link. (Published Online 21 April 2011) DOI 10.1007/s10845-011-0535-3 (2011).
99. A. Azadeh, M. Seifoory, M. Abbasi, Integration of simulation and fuzzy multi-attribute decision making for modeling and assessment of fuzzy parameters, International Journal of Industrial and Systems Engineering, 6 (4) (2010) 483-502.
100. M. Kumar, S.P. Yadav, S. Kumar, A new approach for analyzing the fuzzy system reliability using intuitionistic fuzzy number, International Journal of Industrial and Systems Engineering, 8 (2) (2011) 135-156.
101. Y.M. Ali, L.C. Zhang, Surface roughness prediction of ground components using a fuzzy logic approach, Journal of Materials Processing Technology, 89–90 (1999) 561–568.
102. A. Gupta, H. Singh, A. Aggarwal, Taguchi-fuzzy multi output optimization (MOO) in high speed CNC turning of AISI P-20 tool steel, Expert Systems with Applications, 38 (2011), 6822–6828.
103. J.-S. R. Jang, ANFIS: Adaptive-Network-Based Fuzzy Inference System, Systems, Man and Cybernetics, 23(3) (1993) 665–685.
104. Y. Jiao, S. Lei, Z.J. Pei, E.S. Lee, Fuzzy Adaptive Networks in process modeling: surface roughness prediction for turning operations, International Journal of Machine Tools and Manufacture, 44(15) (2004) 1643–1651.

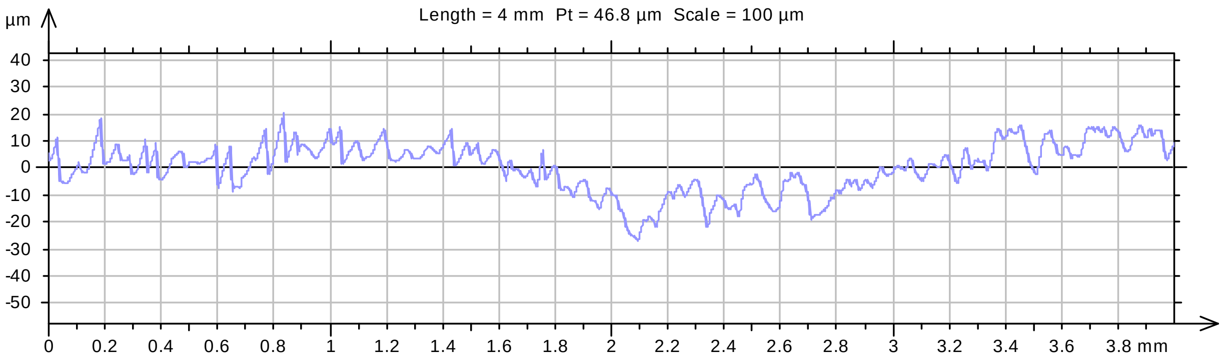
105. J.C. Chen, M. Savage, A fuzzy-net based multi level in Process surface roughness recognition system in milling operation, International Journal of Advanced Manufacturing Technology, 17 (2001) 670–676.

106. S.J. Lou, J.C. Chen, In-Process surface roughness recognition (ISSR) system in end-milling operation, International Journal of Advanced Manufacturing Technology, 15 (1999) 200–209.

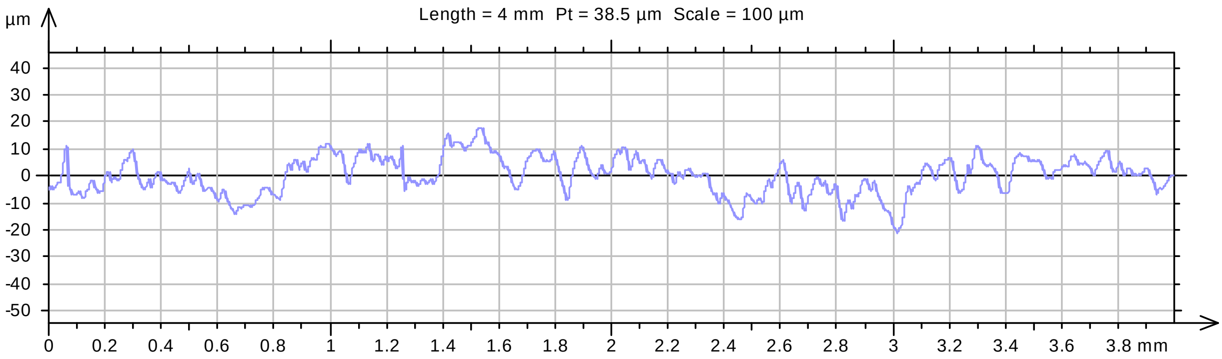
107. B. Lin, M.Z. Zhu, S.Y. Yu, H.T. Zhu, M.X. Lin, Study of synthesis identification in the cutting process with a fuzzy neural network, Journal of Materials Processing Technology, 129 (2002) 131–134.

Appendix

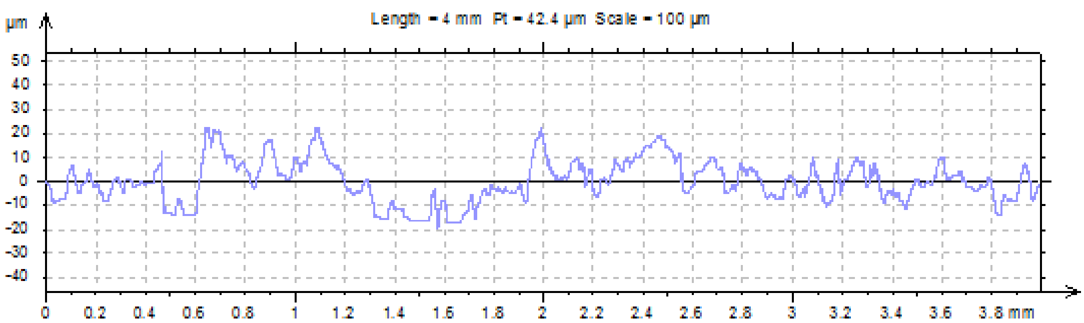
Appendix 1 Roughness profile



Sample No. 1 (Trial 1)



Sample No. 1 (Trial 2)



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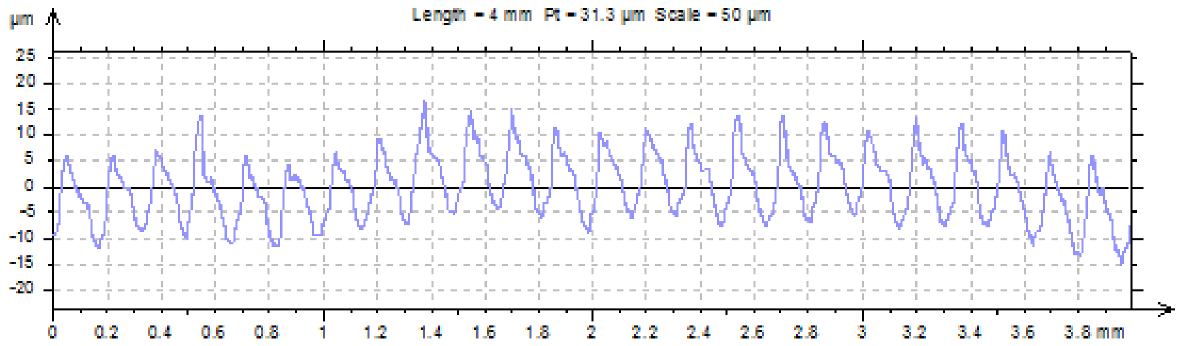

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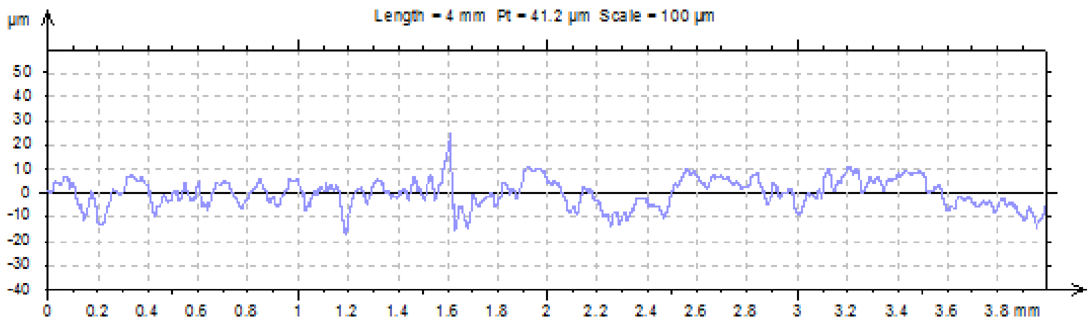

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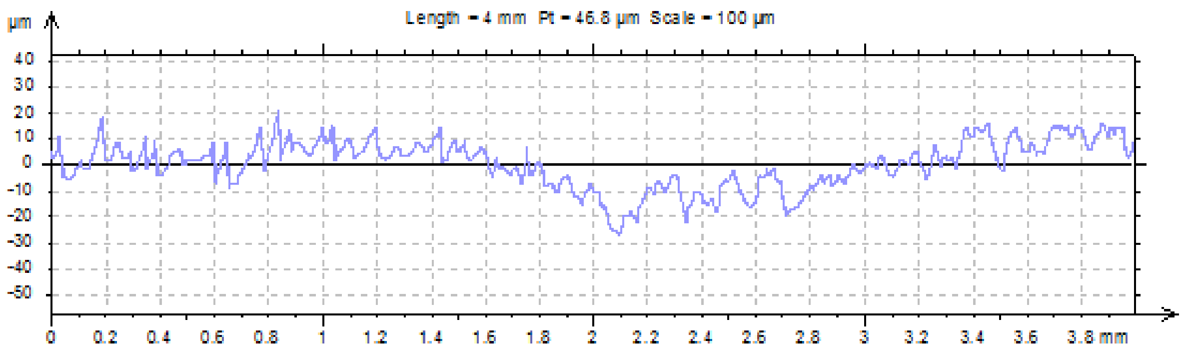

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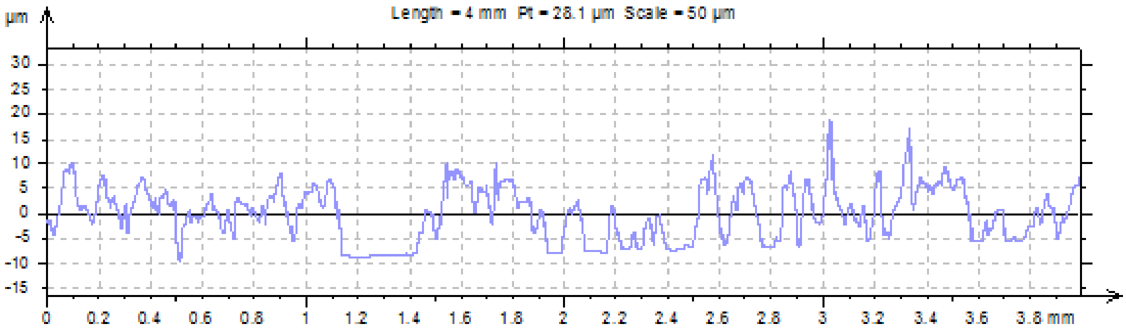

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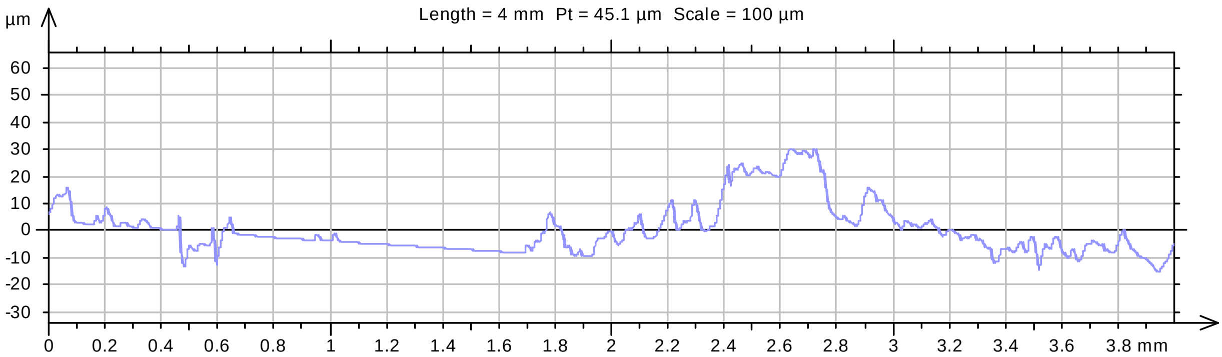

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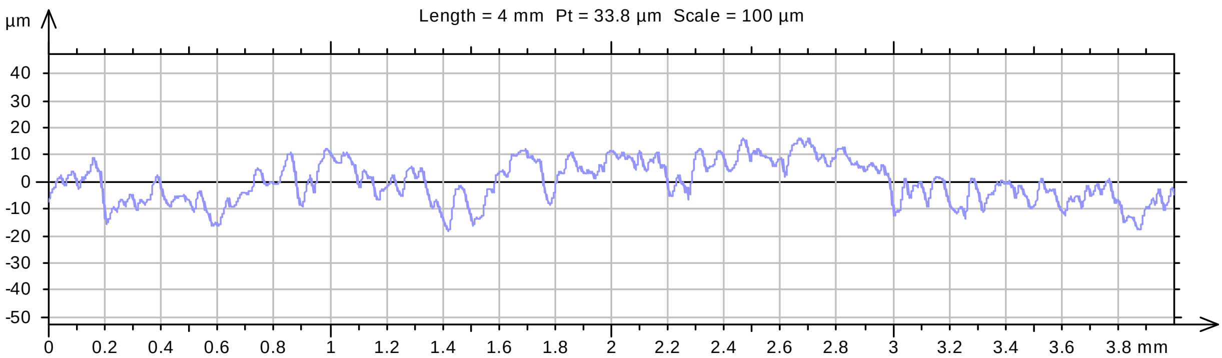

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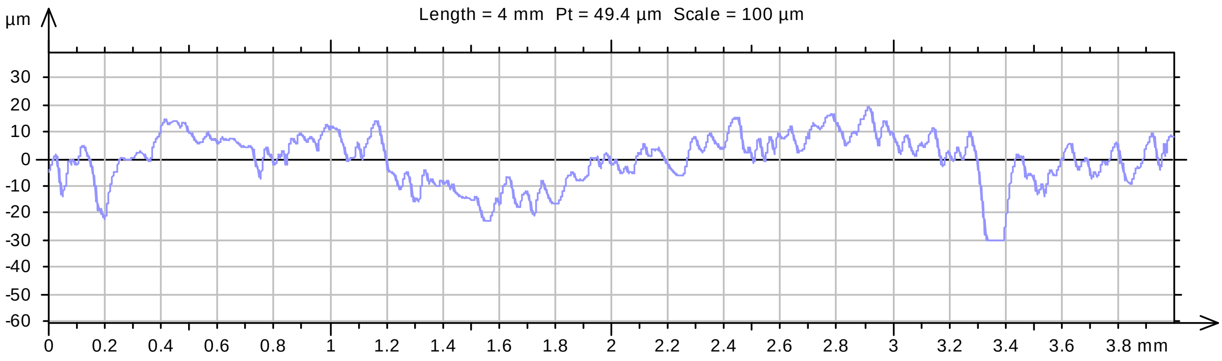

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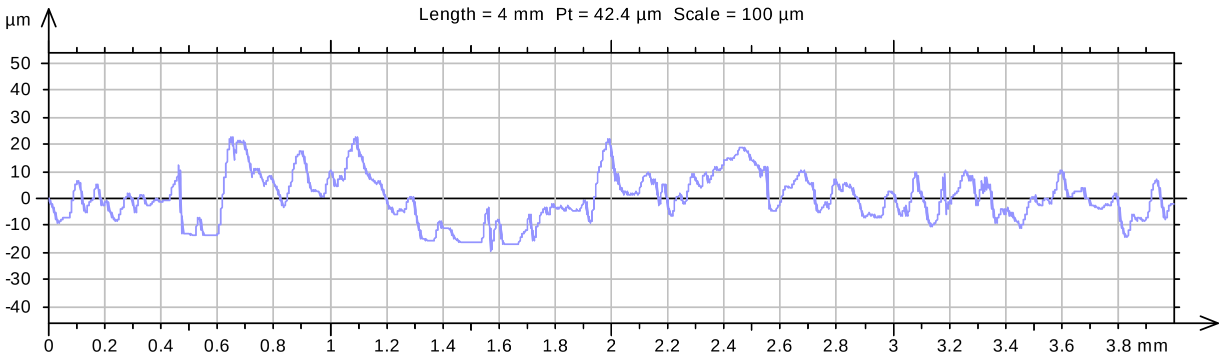

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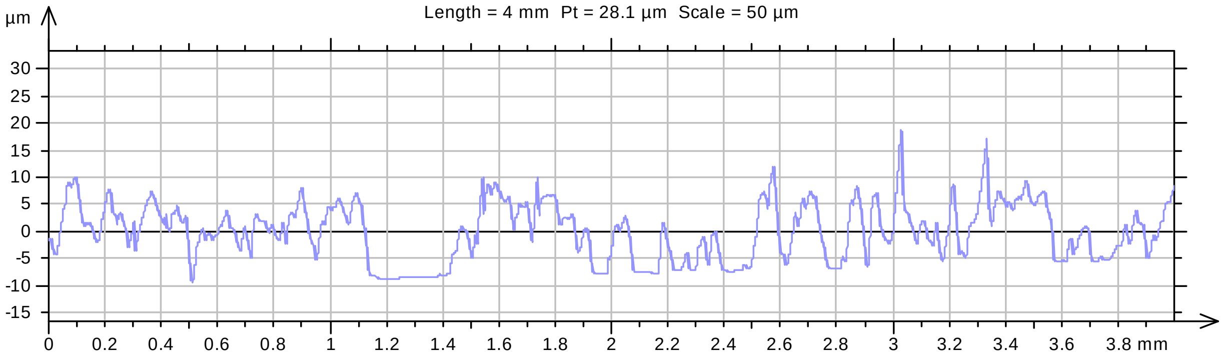
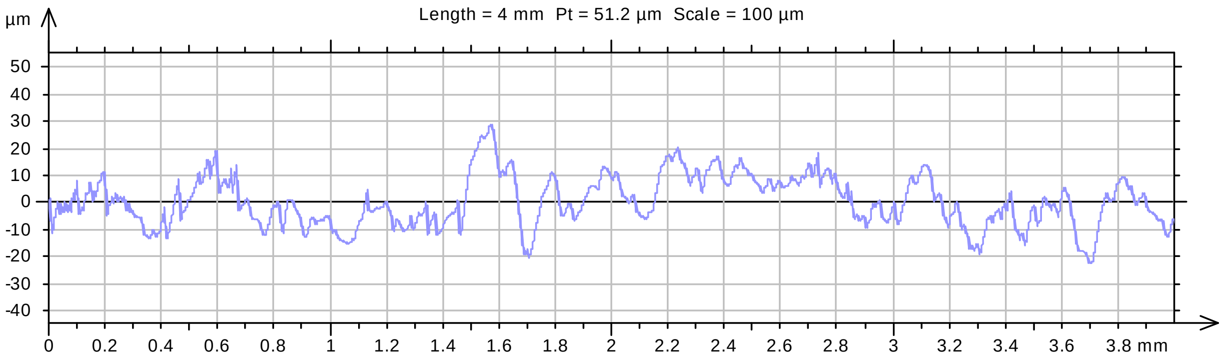
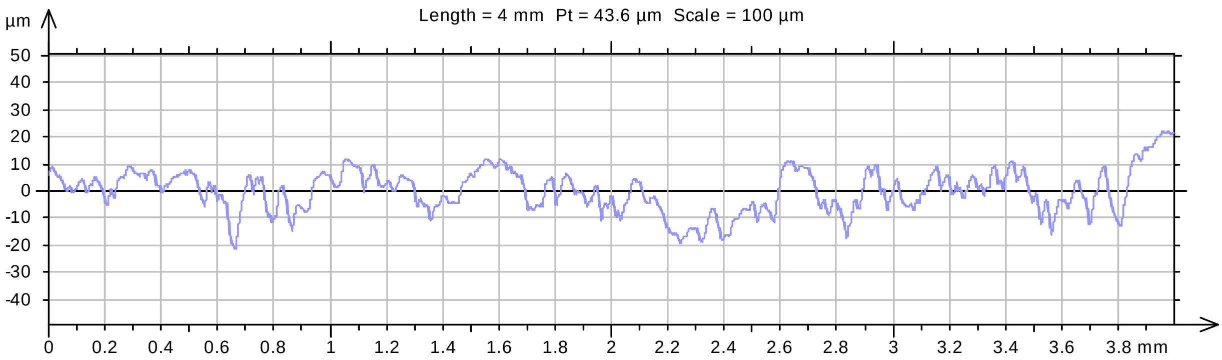


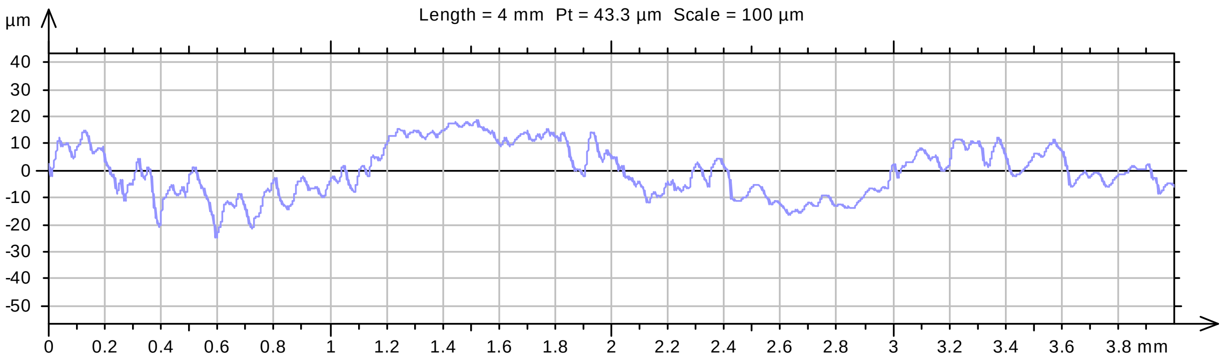
Sample No. 6 (Trial 2)



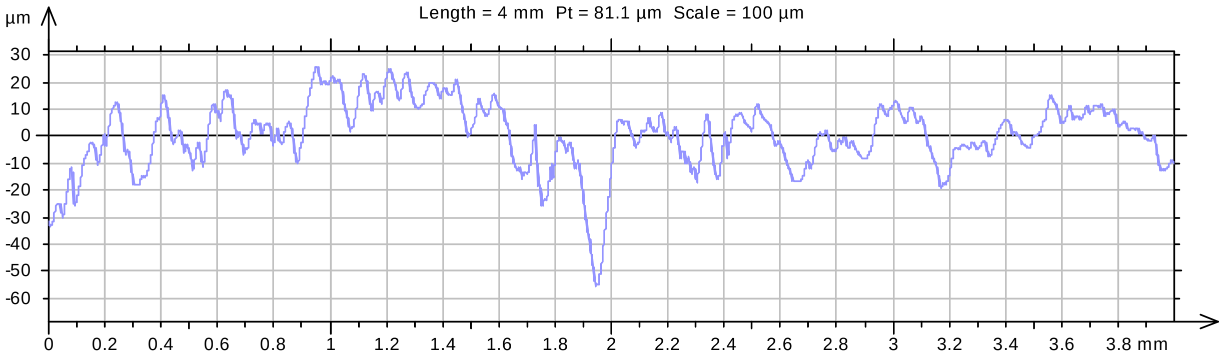
Sample No. 7 (Trial 1)



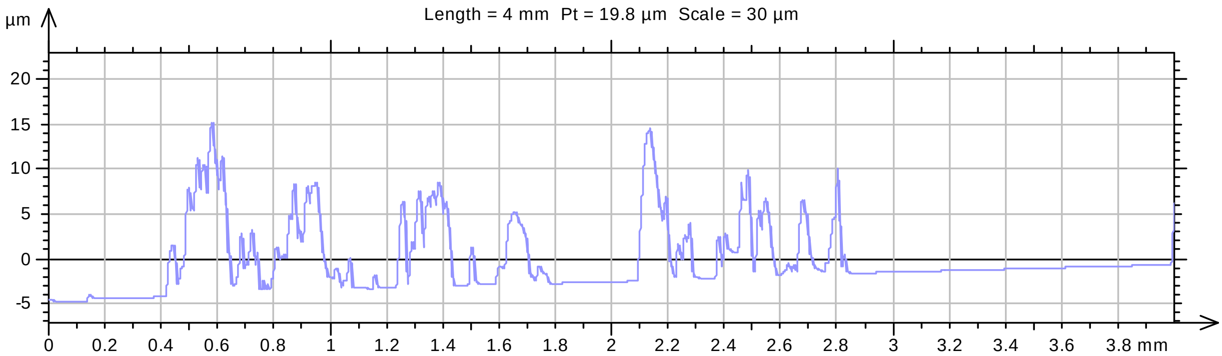
Sample No. 7 (Trial 2)



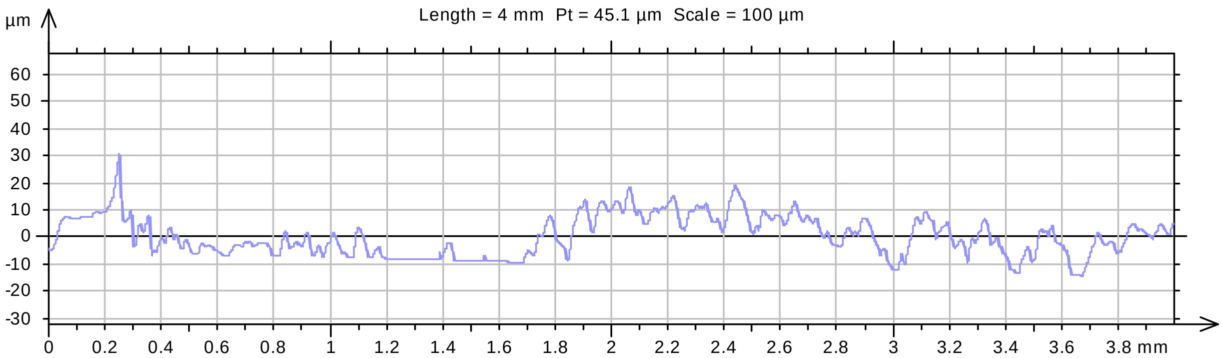
Sample No. 8 (Trial 1)



Sample No. 8 (Trial 2)



Sample No. 9 (Trial 1)



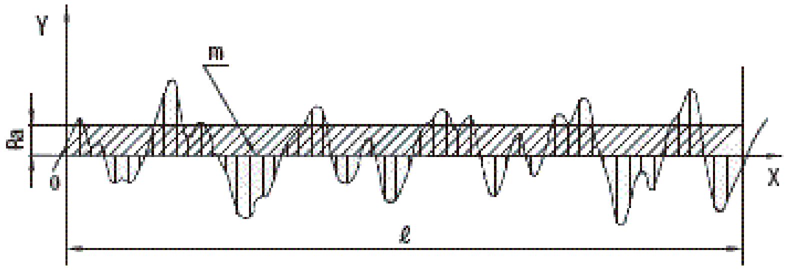
Sample No. 9 (Trial 2)

<u>**Appendix 2 Definitions of various surface roughness features and MRR**</u>

1. R_a (arithmetic average height)

Roughness average R_a is the arithmetic average of the absolute values of the roughness profile ordinates. R_a is the arithmetic mean roughness value from the amounts of all profile values.

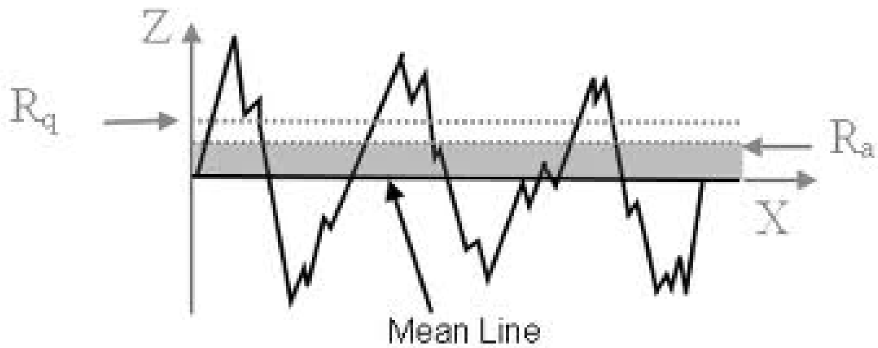
$$R_a = \frac{1}{l}\int_0^l \left|Z(X)\right| dx$$



2. R_q (root mean square roughness)

Root mean square (RMS) roughness R_q is the root mean square average of the roughness profile ordinates. Rq is more sensitive to peaks and valleys then Ra, because the amplitudes are squared.

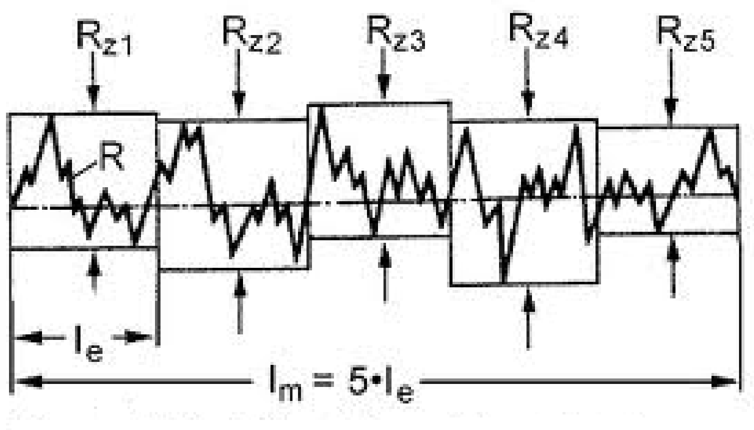
$$R_q = \sqrt{\frac{1}{l}\int_0^l Z^2(X)\, dx}$$



3. R_z (Average Maximum Height of the Profile)

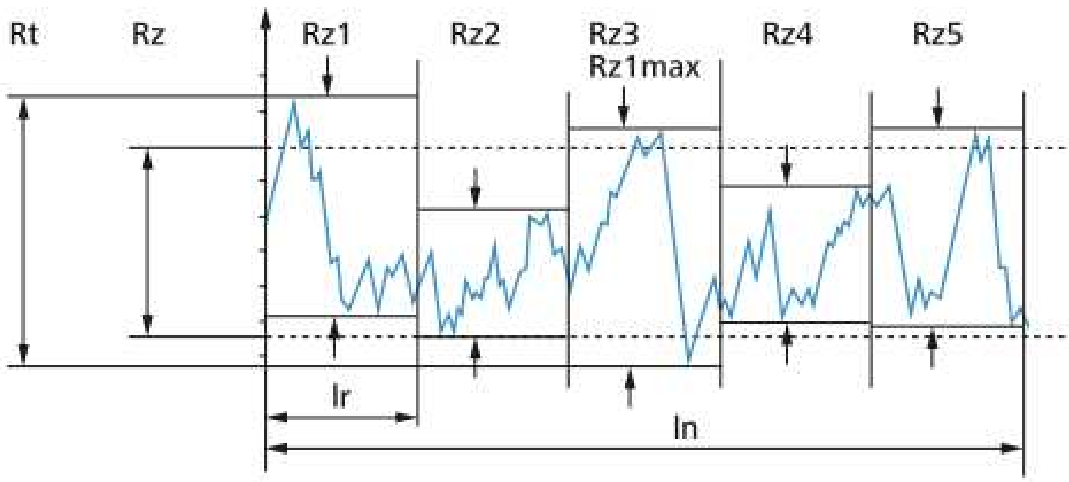
It is the mean of the distance between the highest and lowest points of five successive sample lengths of the roughness profile. It is more sensitive than R_a to changes in surface finish, as maximum profile heights and not averages are being examined. The mean roughness depth R_z is the mean of five roughness depths of five successive sample lengths *l* of the surface roughness. Z is the sum of the height of the highest peaks and the lowest valley depth within a sampling length. R_z is more sensitive than Ra to changes in surface finish as maximum profile heights and not averages are being examined.

$$R_z = \frac{1}{5}\left(R_{z1} + R_{z2} + R_{z3} + R_{z4} + R_{z5}\right)$$



4. R_t (Maximum Height of Profile)

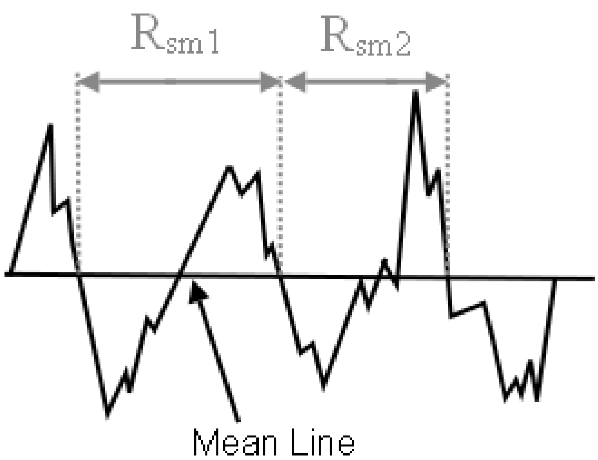
The maximum height of the profile is the distance between the maximum peak height and the maximum valley depth from then mean line in each sampling length. R_z is the mean value of the maximum peak-to-valley heights in the evaluation length. R_t is the distance between the highest peak and the deepest valley of the profile of the total evaluation length.



5. **R_{sm} (Mean width of profile elements)**

It is the arithmetic mean value of the widths of the profile elements of the roughness profile, where a profile element is a peak and valley in the roughness profile. The units of R_{sm} are micrometers or micro inches.

$$R_{sm} = \left(\frac{1}{n} \sum_{i}^{n} S_{mi} \right)$$



6. R_{ku} (Kurtosis of the roughness profile)

It is the quotient of the mean quadratic value of the ordinate value $Z(x)$he fourth power of the P_q, R_q, or W_q respectively, with in a sampling length. It is measure of sharpness of the probability density function of the ordinate value.

$$R_{ku} = \frac{1}{NR_q^4} \sum_{j=1}^{N} r_j^4$$

7. Material Removal Rate (MRR)

Material removal rate (MRR) has been calculated from the difference in weights of the work pieces before and after experiment.

$$MRR = \frac{W_i - W_f}{\rho . t_m} \left(mm^3 / \min \right)$$

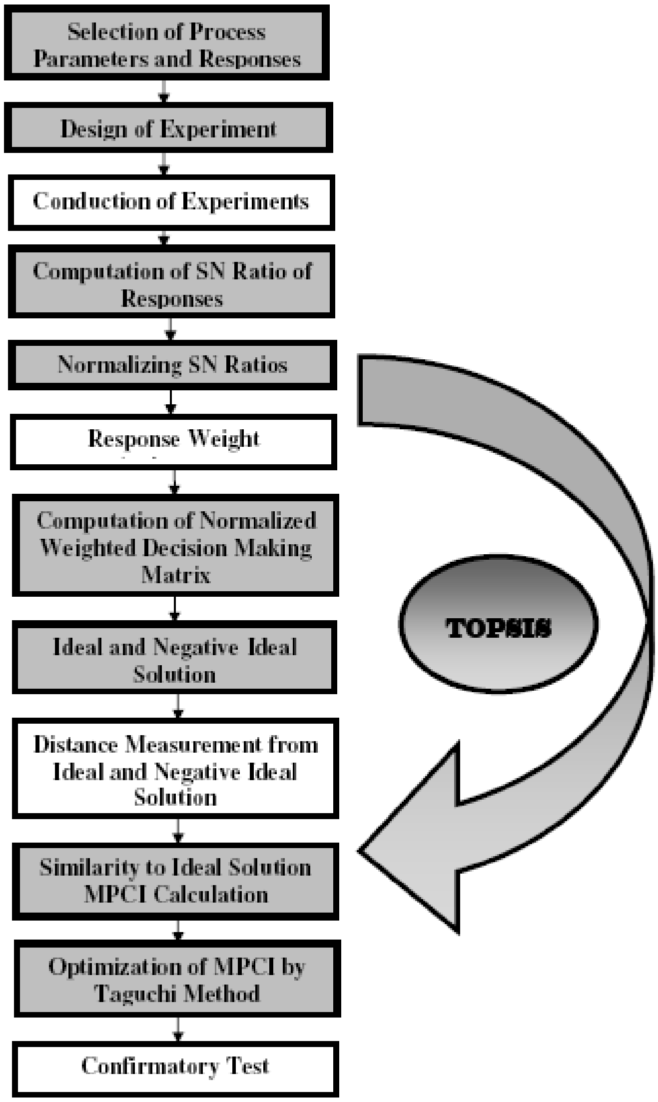
Here, W_i is the initial weight of the work piece in gm

W_f is the final weight of the work piece in gm

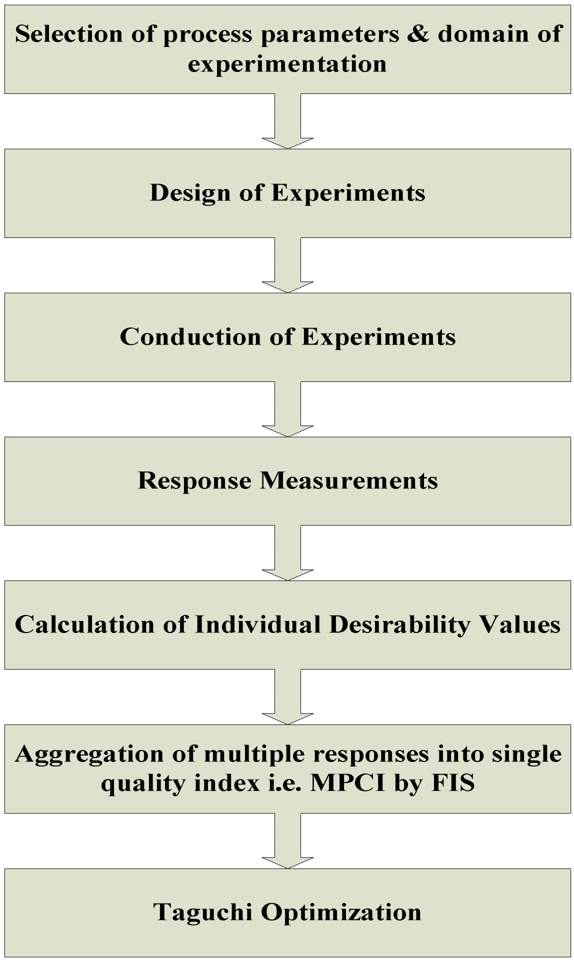
ρ is the density of work material (2 gm/cm^3 for GFRP polyester) and

t_m is the machining time in minute.

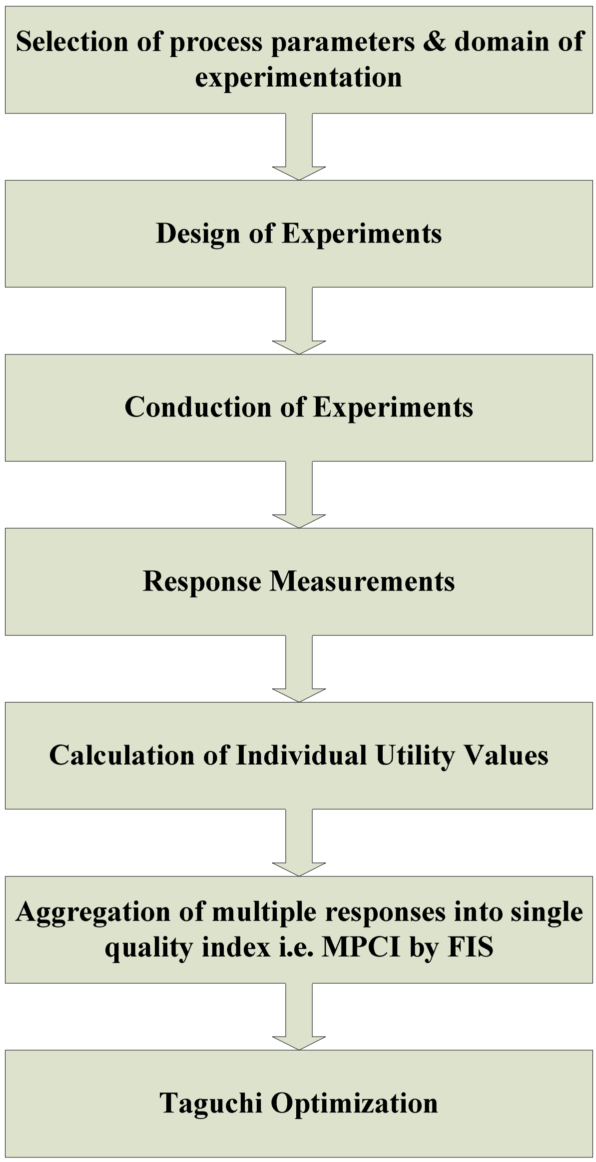
Appendix 3 TOPSIS based Taguchi optimization approach



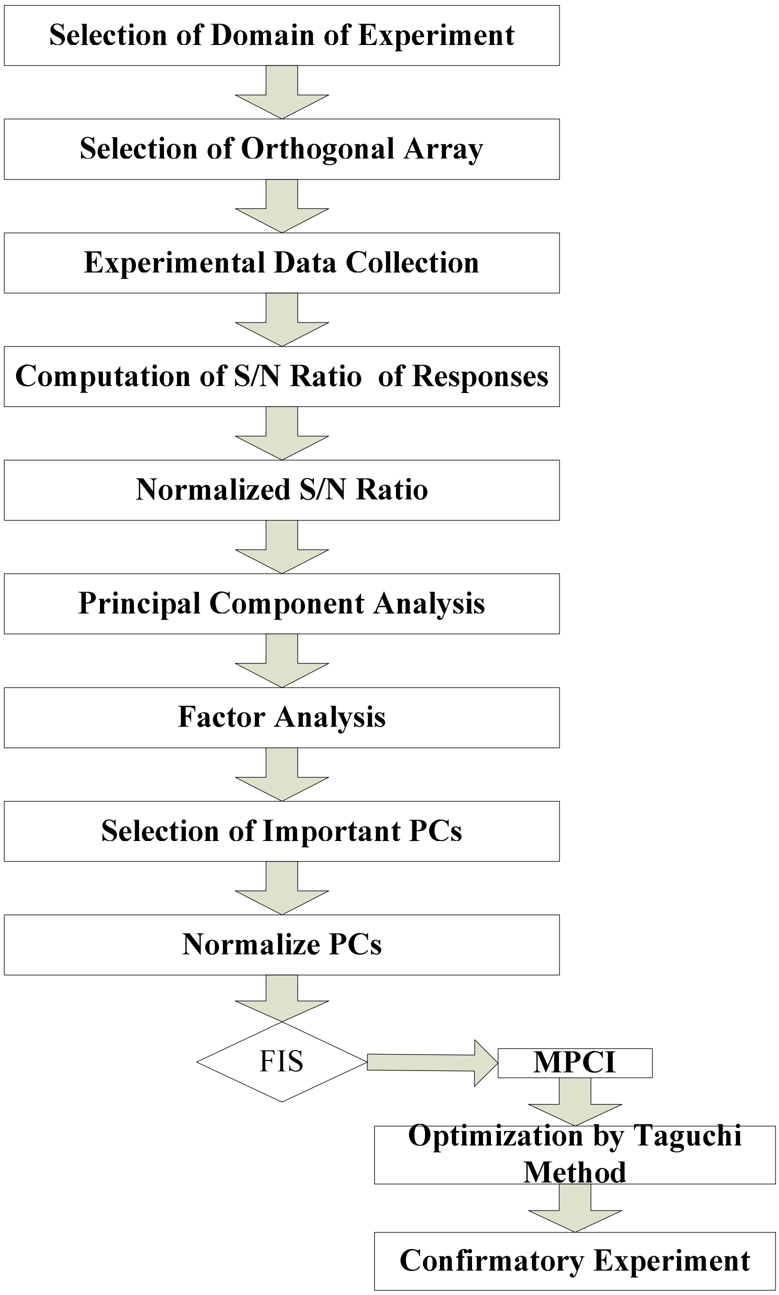
Appendix 4 Desirability Function and Fuzzy based Taguchi optimization approach



Appendix 5 Utility Theory and Fuzzy based Taguchi optimization approach



Appendix 6 PCA Fuzzy based Taguchi optimization approach



List of Publications

Journals

1. **Ankita Singh**, Saurav Datta, Siba Sankar Mahapatra, "*Application of TOPSIS in the Taguchi Method for Optimal Machining Parameter Selection*", 2011, **Journal for Manufacturing Science and Production (JMSP)**, Vol. 11, pp. 49-60, **De Gruyter**, **Germany**.
2. **Ankita Singh**, Saurav Datta, Siba Sankar Mahapatra, "*Principal Component Analysis and Fuzzy Embedded Taguchi Approach for Multi-Response Optimization in Machining of GFRP Polyester Composites: A Case Study*", **International Journal of Industrial and Systems Engineering (IJISE)**, **Inderscience Publishers**. (**In Press**)

Conferences

3. **Ankita Singh**, Saurav Datta, Siba Sankar Mahapatra, "*Application of PCA Based Fuzzy Reasoning Combined with Taguchi's Philosophy In Machining of GFRP Polyester Composites*", Proceedings of the **International Conference on Industrial Applications of Soft Computing Techniques (IIASCT 2011)**, August 20-22, 2011, Bhubaneswar, Orissa.
4. **Ankita Singh**, Ankita Sahu, Saurav Datta, Siba Sankar Mahapatra, "*Aggregation of Multi-responses in Turning Process Optimization on GFRP (Polyester) Composite Using Utility-Fuzzy Approach*", **2nd National Conference on Recent Advances in Manufacturing (RAM-2011)**, 15-17 September 2011, Organized by Department of Mechanical Engineering, SV National Institute of Technology, Surat-395007.
5. **Ankita Singh**, Saurav Datta, Siba Sankar Mahapatra, "*Multi-Objective Optimization of GFRP Composite Using Desirability Function based Fuzzy Approach Coupled with Taguchi Method*", **International Conference on Advances in Supply Chain and Manufacturing Management, Achieving Growth, Profitability and Sustainability in a Globalized Environment (ASCMM 2011)**, December 16-18, 2011, organized by Department of Industrial Engineering and Management, Indian Institute of Technology, Kharagpur.
6. **Ankita Singh**, Kumar Abhishek, Jambeswar Sahu, Saurav Datta, Siba Sankar Mahapatra, "*DEA based Taguchi Approach for Multi-Objective Optimization: A Case Study*", **International Conference on Modeling, Optimization and Computing (ICMOC 2012)**, Noorul Islam University, Noorul Islam Centre for Higher Education, Kumaracoil, Thuckalay, Kanyakumari District, Tamilnadu State, India- 629 180, April 10-11 2012.